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The National University of Ireland

University College Cork

Department of Accounting Finance and Information Systems

Head of Department: Professor Joseph Feller

Supervisors: Bill Emerson and Dr. John McAvoy

The Application of an Immersive Design Process to Investigate Theories for Motion Sickness in Virtual Reality Data Visualisations

Ultan Hill, BSc

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Abstract

Virtual Reality (VR) technology allows a person to be taken from their current environment and into an entirely new, digital and immersive one. Because of this capability, it has been used in several fields as a data visualisation tool to completely immerse researchers and industry professionals in their data. In industry, companies derive value from their data by relying on their employees' ability to create meaningful information from it. Data literacy, in brief, is the ability to effectively manage, use, and understand data to produce meaningful information. However, given the recent increase in volume and complexity of data, the data literacy ability of these employees is now often inadequate. It has been speculated that, by addressing the core pillars of data literacy with VR instead of more traditional 2D visualisations, this problem can be addressed more effectively. This thesis conducts research to examine how this can be done.

A common concern of creating VR visualisations is that they can be problematic to design in terms of the design process used. The design process for immersive visualisations can often be based on trial and error. This is not the optimal process for design as it is more time-consuming and relies on the designer guessing what the client wants instead of relying on requirements and feedback from them. To address this problem, this thesis details a novel design process which was created using the Design Science Research (DSR) methodology. This is then tested and iterated on in a real-world industry collaborative project.

Another concern of creating VR experiences is the adverse effects on the user. Motion sickness is one of the most prominent physiological effects users experience. However, while there have been numerous studies into what causes it and how it can be mitigated, there has yet to be a study into why it occurs in VR data visualisations and how severe it could be. While the Sensory Conflict Theory is the most widely accepted reason for motion sickness in VR games and simulations, it has yet to be determined if this is the case for motion sickness in VR data visualisations. This thesis describes an experiment that was conducted to investigate this issue and determine how severe the effect of motion sickness could be in VR data visualisations.

The research objective of this thesis is to examine how an immersive design process for data visualisation can explain the effects of motion sickness. As a first step, data literacy is examined and, once a more comprehensive understanding is achieved, the research then investigates how VR can theoretically be applied to increasing data literacy.

Once this theoretical grounding is provided, a practical application of VR is then examined which consisted of creating a prototype immersive visualisation in conjunction with State Street to visualise their numerous financial product and service offerings. This project not only resulted in a completed prototype but also in a research chapter detailing the creation of a novel process to design immersive data visualisations.

Once this design process was created, a new research question was discovered in terms of how much of an effect motion sickness can have in VR data visualisations and what are the potential reasons that can cause it to occur. This led to an experiment where two different navigation conditions were implemented to determine the theory that best describes motion sickness in VR data visualisations and how severe motion sickness could be.

Through these chapters, several new insights into immersive technologies and VR can be gained. Firstly, a greater understanding of the relationship between VR and data literacy can be appreciated. Secondly, the thesis shows how to design an immersive visualisation in a more efficient manner. Finally, potential reasons for, and the effect of, motion sickness on users of VR data visualisations are detailed.

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Declaration

The author declares that except where duly acknowledged, this thesis is entirely his own work and has not been submitted for any degree in the National University of Ireland, Cork or any other University.

Acknowledgements

I would like to firstly thank my fellow students in the Fintech masters for making it such a great year and for being a great group of friends. I would also like to thank my supervisors John and Bill for working so hard on this thesis and being invaluable in getting this done to a high-quality standard. I'd also like to thank State Street for funding the course and specifically to Brian and Neasa for working with us throughout the year and giving me so much experience working with industry on top of the research experience. Last, but definitely not least, I want to thank: my parents Colin and Dymphna, my brother Cian and my sisters Grainne and Daragh and all my friends. They were all a constant source of advice and support whenever I needed them and were a real lifeline for me.

1. Introduction

While Virtual Reality (VR) is still an emerging field of research, VR itself has been around since the 1960's when Ivan Sutherland created his "Ultimate Display" headset (Sutherland, 1965). VR research and development continued in the 1980's when NASA created their own headset (Fisher, 1986) which had much of the same functionality as modern head mounted displays (HMD's). These could be controlled through the user's position, voice, and gesture and allowed the user to interact with a 360-degree digital environment. In the 1990's game companies such as Sega and Nintendo created their own VR HMDs: the SegaVR and Nintendo Virtual Boy (Hill, 2014; Boyer, 2009). However, they were not commercially successful, and both were eventually discontinued.

It wasn't until the 2012 Kickstarter campaign of the Oculus Rift that VR was brought to the general public and eventually gave rise to the creation of several successful VR headsets such as the HTC Vive (Greenwald, 2017). The 2019 Q1 sales of VR and Augmented Reality (AR) headsets have increased by 27.2% over the same period in 2018. 96.6% of those sales come from VR headsets while total AR and VR shipments for 2019 are expected to be around 7.6 million units (Mott, 2019). With Sony having sold a total of 4.2 million PSVR systems, as of March 2019 (Moon, 2019), and Oculus projected to sell 1.3 million units of its wireless Go system in 2019 (Fogel, 2019), VR is becoming increasingly widespread. Research into potential applications and challenges of VR headsets has been ongoing and ranges from applying it to stroke rehabilitation (Laver et al., 2017) to examining their potential use as a communication tool in financial services (Campbell, 2019).

How VR could be used to help a person to understand their data and to gain more meaningful information from data (referred to as data literacy) is an increasingly important area. This is because datasets have become larger and more complex to the point where traditional 2D tools have been found to be inadequate to cope. Therefore, a new tool is needed and VR has the potential to be that tool.

Before VR can be of benefit to areas such as data literacy, the development of the systems needs to be considered. An issue with VR data visualisations is the lack of a design process to follow that is specific to these types of visualisations. Even if a process is available, there are further issues with using VR for data visualisations. There is still the issue of motion sickness in these visualisations, how it is caused and how severe it could be. The research objective of this thesis is to examine how an immersive design process for data visualisation can explain the effects of motion sickness.

1.1 Background to the Research

Collaboration with State Street on a real-world problem was a very important part of the masters programme and formed the basis for this thesis. As part of my research, I worked with State Street to tackle real-world business problems. Initially, State Street needed a way to visualise their financial products and services to their clients to make it easier to understand State Street's offerings and what the client required based on their circumstance and specific interests. Therefore, State Street required a VR experience they could use to showcase their product offerings. Screenshots of the finalized prototype can be seen in *Appendix 2* and example reports written for State Street during this collaboration for previous versions of the prototype can be seen in *Appendix 3*. The final prototype was presented at a State Street showcase event, the poster and slides for which can be seen in *Appendix 4*.

During the course of creating this visualisation, three research questions were uncovered. The first research question (Research Question 1 in section 1.3 of this thesis) was how VR benefits the concept of data literacy? How can it be used to provide benefits that more traditional 2D tools can't? Once it was known how VR could benefit data literacy, there remained the question of how to actually implement this. This led to the second research question (Research Question 2 in section 1.3) which examined how the process for designing data visualisations could be improved for immersive visualisations. How could an immersive visualisation design process make the creation of immersive data visualisations more efficient? Once the process was created, refined, and used, there was still the issue of how a user might physiologically react to such a visualisation. The final question (Research Question 3 in section 1.3) examined the effect motion sickness could have in VR data visualisations and the potential reason for it happening. Is motion sickness in VR data visualisations explained by the Sensory Conflict Theory as it is for VR games and simulations or could it be something else?

1.2 Individual Contribution

In this section I will explain my contribution to answering each of the research questions. The work for State Street was predominately based in research teams so there was collaboration on elements of the research. For Chapter 2, I conducted the literature review to gain an understanding of data literacy and the primary concepts involved in it. I also created the Concept Centric Matrix, analysed and separated the concepts into the two groupings and compared 2D tools with VR tools in terms of the "imaginative" group.

In Chapter 3, I created the links between the concepts in the CCM and the iterations of the design process. I analysed the concepts to determine their relationship to the initial process steps. I also analysed the process steps of both iterations of the process, determining the relationship between the steps in both processes and how they changed in the second iteration. I was also heavily involved with the practical application of the process to the real-world business problem. I analysed the client feedback to gain a better understanding of State Street's requirements and how to alter the process to make it more efficient.

The research described in Chapter 4 is solely the work of the thesis author.

1.3 Research Questions

The research objective of this thesis is to examine how an immersive design process for data visualisation can explain the effects of motion sickness.

While the objective describes the overarching goal of the thesis, three research questions represent the individual elements that combine to meet the research objective. The three research questions are:

> Research Question 1: How does VR benefit the concept of data literacy?
>
> Research Question 2: How can the process for designing data visualisations be improved upon for immersive visualisations?
>
> Research Question 3: How much of an effect does motion sickness have in VR data visualisations and what is the potential reason behind what causes it?

These research questions are directly addressed in different chapters in the thesis.

- Research Question 1 is addressed in Chapter 2.
- Research Question 2 is addressed in Chapter 3.
- Research Question 3 is addressed in Chapter 4.

What follows is a brief description of each chapter as they relate to the research questions.

The research in Chapter 2, as it relates to Research Question 1, found that there are two primary conceptual groups that constitute data literacy: “functional” and “imaginative”. While VR applies to the “imaginative” group, it is not relevant to the “functional” group. When creating immersive visualisations, it is this “imaginative” conceptual group that should be focused on as they relate more to visualising and explaining data. The “imaginative” group comprises four concepts that relate to data literacy. They are: “Discovery of Patterns”, “Understanding”, “Visualise” and “Explanation”. It was found that each of these concepts can benefit from the application of VR instead of traditional 2D visualisations. The exception to this was the concept of “Explanation” where it was found that traditional 2D tools also have a benefit.

Research in Chapter 3 led to the creation of a new design process for immersive visualisations. This new process was found to make the creation of immersive data visualisations more efficient. It was determined that the process needs to be cyclical to obtain multiple rounds of feedback from the client. This ensures that time is not wasted on designs that do not address what the client wants. Based on this, the need for prototyping was critical, specifically immersive prototypes. The importance of these immersive prototypes became clear as they allowed the client to “see” the visualisation. This in turn helped them to better understand the visualisation, determine its capabilities, and refine their requirements.

Finally, research in Chapter 4 examined in detail one aspect of VR data visualisations that can present problems, even if the correct development process is used. Based on existing research into VR in general, it was determined that motion sickness occurring in VR data visualisations is most likely to be the Sensory Conflict Theory. An experiment was conducted to investigate if the theory also applied in VR data visualisations.

1.4 Research Methods

Several different research methods were employed for this research with each method chosen to address the relevant research question.

For Chapter 2, an extensive literature review was conducted to gain an understanding of what data literacy is and how it has been defined. A Concept Centric Matrix (CCM) was used to identify the important concepts of data literacy and to then focus on how VR can be used to benefit it.

In Chapter 3, the research followed the Design Science Research methodology. An artefact was created and applied to a real-world problem. The artefact was created and refined using a new design process for immersive data visualisations created as part of this research. This was then applied to a real-world business problem. A CCM was also created to isolate the most important concepts that relate to the design of immersive visualisations.

In Chapter 4, an experiment was used as the research method. This experiment was carried out to test whether the Sensory Conflict Theory is the best explanation for motion sickness in VR data visualisations. Before this experiment was conducted, an extensive literature review was conducted into the various theories explaining the causes of motion sickness.

1.5 Choice of Research Topic

The goal of this research is to investigate immersive data visualisations and to examine whether the same theory behind motion sickness in more "traditional" experiences, such as virtual reality games, also apply to immersive data visualisations. While VR has been around in some form since the 1960's, the potential of the technology has only been widely investigated in the last ten years.

There have been numerous studies into the potential uses of VR and its potential benefits over more traditional visualisation methods. There have also been numerous studies into the side effects of VR usage; chief among them being motion sickness.

Neck fatigue and eye strain are common symptoms of prolonged VR use, but motion sickness is the most prevalent and can, for some users, cause nausea and vomiting. How to minimise the effects of motion sickness has been investigated widely because of these health concerns and several theories have been proposed to explain why it happens.

These studies are predominantly concerned with content such as games or immersive experiences and these do not necessarily also describe the effect of motion sickness specifically on data visualisations. It is unclear whether motion sickness is a factor in immersive data visualisations and, if it is, how severe can it be? Sensory Conflict Theory is the most widely accepted explanation for motion sickness in VR, but it is not clear if it is a good theory for explaining motion sickness in VR used for data visualisation.

VR is a potentially very powerful tool for data exploration as the complexity and abundance of data is growing rapidly with the rise of “Big Data”. Therefore, potential side effects of the use of immersive data visualisations needs to be explored and a better understanding of why it occurs is necessary. This thesis sets out to establish if motion sickness is a side effect of immersive data visualisations and suggests the most likely theory to explain its occurrence. In so doing, it aims to provide a basis to the understanding of motion sickness in immersive data visualisations.

2. Improving Data Literacy Through the Use of Virtual Reality

Abstract

The aim of this chapter is to examine how Virtual Reality (VR) can benefit data literacy. Data literacy is an individual’s ability to correctly source, collect, and manipulate data to produce meaningful information. VR has the potential to benefit elements of data literacy. A literature review conducted in this chapter revealed several concepts that are core to the definition of data literacy. Some of the concepts that were found, such as curating and managing, are related to sourcing and collecting data. For the purposes of this chapter, these concepts are put in a group called “functional” concepts because they need to be considered to ensure the correct data is being used. The other concepts identified, such as visualising and explaining, are related to displaying data and are put in a separate group called “imaginative” concepts. These “imaginative” concepts need to be considered to ensure as much correct information is identified from the data as is possible. It is in relation to these “imaginative” concepts that VR could provide a benefit to data literacy. This chapter will explain how VR can provide unique benefits, when compared to traditional 2D visualisations, to these “imaginative” concepts while also explaining the areas where 2D can be suitable.

2.1 Introduction

Data literacy can be simply defined as the ability to source, collect and manipulate data to produce useful information. This chapter will illustrate how data literacy consists of several core concepts which can be separated into "functional" and "imaginative" concepts. "Functional" concepts relate to the correct sourcing and managing of data to ensure that the correct data is being analysed. "Imaginative" concepts relate to the visualisation of data to provide usable information. Furthermore, this chapter will also explore how data literacy can benefit from the application of Virtual Reality (VR) and, in particular, how the "imaginative" concepts can be refined and improved with this technology. VR allows a person using an appropriate headset to enter and visualise a virtual world. Using an input device, an individual can move through this virtual world while remaining stationary in their real environment.

Before examining how VR can be applied to help to address these deficiencies, a comprehensive understanding of the term "data literacy" is essential. Data literacy has become an important issue in recent years. By 2020, 50% of all organizations are expected to have insufficient data literacy skills (Panetta, 2019). It is also expected that 80% of organizations will have tried to address these deficiencies in data literacy by then (Hippold, 2018). Despite its importance, there is no standardised definition and so one will be created for the purposes of this chapter. The terms "data" and "literacy" will first be considered separately to provide an understanding of how this definition was created.

Firstly, it is important to distinguish between "data" and "information". Chen et al (2008, p.1) define data as "attributes of real or simulated entities" and information as "data that represents the result of a computational process". These definitions are based on work by Ackoff (1989) who states more plainly that information is processed data. This is the distinction that will be used in this chapter. The recent accumulation of large and complex datasets has led to the rise of "big data". This brings with it two categories of challenges: technical and intellectual. The technical challenge is that large amounts of data can be difficult to store and analyse in traditional databases (Hashem, 2015). The intellectual challenge is how to understand the large amounts of data that have been obtained (Storey, 2017). The technical challenge is beyond the scope of this chapter and will not be considered further in order to concentrate on the relationship between VR and the intellectual challenge of processing and understanding big data. Letouzé et al. (2015) suggest that the term big data is a misnomer and that it is simply a series of related data points that happen to make up very large data sets. The largest difference between "data" and "big data" is the volume of the data in the data set. For the purposes of this chapter the terms "big data" and "data" are considered to be synonymous.

There are multiple interpretations of the term 'literacy'. It is important not to exclude any of these interpretations when defining data literacy because VR could potentially be useful in any of the instances. Laugksch (2000) has suggested that there are three different interpretations of literacy. The original meaning derives from the Latin term *litteratus* which classically meant a person who was well educated or learned (Clanchy, 1979). Another interpretation is that one is adequately qualified (Teodorescu, 2006), suggesting that literacy means that one possesses an intermediate level of ability or competence. Finally, literacy has been defined as having only enough knowledge to function in a role in society (Miller, 1989). In terms of the Miller (1989) interpretation, VR could prove a useful tool in engaging students in order to introduce new scientific concepts in an immersive, multimodal format (Hutchison, 2018). At a "competent" level of literacy, Massis (2015) concluded that students can benefit immeasurably when information is delivered through VR. The use of this cutting-edge technology can assist students to become more proficient in their information literacy skills.

Literacy has also been defined by the National Assessment of Adult Literacy (NAAL) as the ability to use printed and written information to function in society, achieve goals, and develop knowledge and potential (White and Dillow, 2005). This definition is useful because it encompasses all three interpretations of literacy, from functioning in society to becoming well educated or learned. By replacing "printed and written information" with "data", data literacy can be defined as the ability to use data to function in society, to achieve one's goals, and to develop one's knowledge and potential. However, a comprehensive definition of data literacy should also include information on where the data can be found, how it can be used and what sources are deemed reputable (Frank et al., 2016). Therefore, the definition needs to be expanded to include these elements. Data needs to be sourced from the right places, used and manipulated in a logical and unbiased method, and the resulting information needs to provide some meaningful benefit in terms of actionable decision-making. This leads to the following definition of data literacy that will be used in this chapter:

"*Data literacy describes an individual's ability to correctly source, collect, and manipulate high-quality data to produce meaningful information in order to expand their existing knowledge in an area of research or to aid in their decision-making process to achieve their goal.*"

2.2 Methodology

In order to conduct an examination of the relationship between data literacy and VR, a systematic literature review using a Concept Centric Matrix (CCM) was carried out into data literacy. This literature review followed the process as laid out by Webster and Watson (2002). The concepts from the literature identified as significant were found by searching for the terms 'data literacy', 'information literacy', 'big data', 'differences between information and data', 'big data and data literacy', 'virtual reality and literacy', 'immersive technology and literacy', 'scientific literacy', 'statistical literacy', and 'functional literacy'. These searches were conducted on Google Scholar, EBSCO, and the AIS electronic library. Over 165 results were generated, of which half were considered irrelevant due to the content not being applicable to this research. Of the remaining papers, by reading the abstract of the papers, 80 papers were considered useful.

Further research was carried out by way of searches for data literacy, statistical, scientific and information literacy in order to find additional definitions of data literacy separate to the initial results in order to extract as many key concepts as possible, the results of which were compiled in a CCM following the process outlined by Webster and Watson (2002). The only exceptions to this rule are the Schneider (2013) and Qin and D'Ignazio (2010) definitions because they were deemed to be more granular and specific definitions of data literacy. Searches for 'pattern discovery in virtual reality', 'virtual reality and pattern recognition', 'virtual reality understanding of data', 'virtual reality visualisation of data', 'virtual reality and explanation of data' on Google Scholar, EBSCO and AIS electronic library generated over 100 results, of which 30 were considered to be useful for the research because they could be applied to this research. Following on from this, these papers were then analysed and categorised to clarify how VR could be used to benefit those concepts and therefore data literacy.

2.3 Data Literacy

As illustrated by *Table 1*, after analysis of existing literature, eight core concepts were identified. Through further refinement, these concepts were divided into two general categories: “functional” concepts and “imaginative” concepts. The “functional” concepts category is made up of the curation, management, decision making and analysis concepts, while the “imaginative” concepts category consists of the discovery of patterns, understanding, visualising and explaining concepts. These categories serve to distinguish between those that might be affected and enhanced by VR and those that might not. “Functional” concepts are those that need to be considered to ensure the right data is gathered and that analytics is performed on them accurately and correctly. These concepts rely on actions that need to be performed on the data in order to ensure accurate and relevant results will arise from any analysis performed on them and as such were not considered to benefit from the application of VR. However, the “imaginative” concepts are those that require more creativity and understanding to display, find relevant patterns from, and draw meaningful insights from the data which can be enhanced through the use of VR (see *Table 2*).

Definitions/Concepts	Curation	Management	Decision Making	Analysis	Discovery of Patterns	Understanding	Visualize	Explanation
McAuley et al. 2014	X							X
Mandinach et al. 2008			X			X		X
Calzada Prado and Marzal 2013		X	X					
Deahl 2017	X					X	X	X
Carlson 2011						X		
Schneider 2013 *		X		X	X		X	
Qin and D'Ignazio 2010 **		X	X			X		
Johnson 2012			X		X		X	
Wolff et al 2016								X
Panetta 2019				X		X	X	X
Smit 2015		X			X			X
Sternkopf 2018				X	X			
Bhargava 2015						X		X
D'Ignazio and Bhargava 2016				X	X			X
ODI 2016				X		X	X	X
Weigend 2017			X			X		
Okamoto 2017	X	X					X	X
Gray et al. 2012				X	X	X		X
Gemignani 2014				X	X	X		
Gartner 2018				X				X
Love et al. 2008			X		X			X
Carroll and Carroll 2015			X	X				X
Mandinach et al. 2016	X			X		X		
Bowen and Bartley 2013			X	X				X
Fontichiaro et al. 2017					X	X		

Table 1. Data Literacy Concept Matrix

Curation, in this context, takes its meaning from the description of data archiving by Lord et al. (2004) as being the ability to identify, retrieve and collect data all in one logical place. It refers to knowing where to find data as well as having a depository to store that data for it to be queried and sorted. The management concept refers to the querying of data for problem solving and decision support (Abadi, 2009). It also includes the acquisition and processing of that data so that they can be disseminated according to specific standards (Gharaibeh et al, 2017). Once the data has been processed according to those standards, decisions must then be made as to which data is of sufficient quality to be "fit for use" (Wang and Strong, 1996, p.6).

The data that has been gathered and sorted may not always be relevant to the problem at hand and so the users of the data must decide which to include in their eventual analyses (Wang and Strong, 1996, p.6). Following this, the data is analysed according to the "area of investigation and the research question" (Johnston, 2017, p.620) they are looking to answer. For the purposes and scope of this research, these "functional" concepts are not considered to be relevant to the application of VR and as such will not be considered as part of the comparison between VR and 2D with regard to data literacy below. "Functional" concepts are not suited because they are more centred around analysis and data gathering whereas the "imaginative" concepts focus more on displaying and visualising data which is a central pillar of VR technology.

These "imaginative" concepts require more creativity and could benefit most from being applied to a VR setting because they are more visually oriented; therefore, they will be examined further in this chapter. Once the necessary and required analysis has been performed on data, patterns and relationships will start to be revealed within it. These patterns will illustrate whether there is a connection among the data that warrants more attention or not. If there are patterns, they then need to be deduced and any meaning derived from them. Once the meaning behind the pattern is understood, it may then have to be shown to others in order to inform a decision or to uncover new knowledge. In order to do this, the information must be visualised and explained. *Table 2* below illustrates how VR has the potential to do this. The section that follows will briefly recount the history of VR before examining how VR can provide benefits to the "imaginative" concepts.

2.4 2D vs VR Visualisation

Because data literacy is set to become an important challenge in the next few years, research been carried out (Smit et al., 2015) into the suitability of new methods and tools of approaching the issue in order to determine whether they are a suitable fit for potential use in the future. One such tool with the potential to impact on data literacy is VR. The potential applications of VR, while not limitless, are incredibly varied. Over the last number of years, it has been applied to differing areas such as palaeontology (Laha et al. 2014) and HIV stigma reduction (Toppenberg et al., 2019). Of all the applications of VR that have been studied, its applicability to data literacy has not yet been examined.

While VR may seem like a new technology, it has in fact been around in one form or another since the 1960's when Ivan Sutherland created "The Ultimate Display" (Sutherland, 1965). VR has become more popular in the last decade, beginning with the Kickstarter campaign to launch the Oculus Rift in 2012 (Kickstarter, 2012). Since then, VR has seen an increase in popularity as evidenced by Facebook's purchase of Oculus only two years later in 2014 for $2 billion (Dredge, 2014). There have also, since then, been entries into this market by Google, HTC and Sony with the Cardboard, Vive, and PSVR (Ralph, 2015; Greenwald, 2017; Rubin, 2019). While these companies have been primarily invested in the creation of content such as games and immersive experiences, and research has been done into the potential of VR in varying industries, there is yet to be an examination of its benefit to data literacy. *Table 2* below describes, using the "imaginative" concepts from the concept centric matrix in *Table 1*, how VR can benefit data literacy.

The concepts that will be examined are those that offer the ability to discover patterns, provide more understanding, visualise more effectively, and act as an aid in explaining data. These "imaginative" concepts were chosen because, as stated earlier, these concepts are more applicable to VR than the "functional" concepts which are more concerned with analysis. *Table 2* illustrates that the relationship between data literacy and VR is based on these concepts. The question of whether to use VR instead of more traditional methods can be difficult to answer (Dübel et al., 2014). VR will not be well suited to all situations, just as any tool isn't suited to every situation. The comparison between VR and traditional visualisations is done to highlight how the benefits to data literacy that are provided by VR can't be found in more traditional visualisations and therefore provide a unique benefit. *Table 2* is a comparison between data representations in a 2D format and in a VR format as they relate to data literacy.

It is acknowledged that 2D can also involve 3D stereoscopic displays on a 2D medium such as a screen. For the purposes of this chapter they will be considered as 2D visualisations because they are not fully immersive in that the user is still in their "real environment" looking at a 2D display rather than being in a completely virtual world where they can experience a sense of immersion in their data. The chapter also acknowledges that there are occasions where 2D provides benefits over immersive visualisations, however, it will be solely focusing on the benefits immersive visualisations provide over 2D.

	2D Visualisation	*Virtual Reality*
Discovery of Patterns		VR can be used to enhance human pattern recognition and the creation of effective data visualisations (Donalek et al., 2014).
Understanding		Fewer inaccurate insights were reported when using a VR visualisation (Millais et al., 2018).
Visualise		VR is the method of choice when showing realistic impressions of objects or locations (Bergmann et al., 2017).
Explanation	2D representations are preferable to 3D ones for precise measurement or accurate comparison of data values (Marriott and Chen et al., 2018).	Immersive 3D displays can use depth to explain additional abstract information (Marriott and Chen et al., 2018).

Table 2. Comparison of 2D and VR in relation to the "Imaginative" concepts

Having provided an overview of how VR can provide unique benefits to the "imaginative" concepts in *Table 2* above, this section will now go into greater detail into these benefits.

2.4.1 Discovery of Patterns

The rise in the volume of data available is growing to an extent where data being used for analytical purposes is "on the cusp of petabytes" (Russom p.15, 2011). With this growth in data comes the challenge of attempting to understand it by drawing patterns from it, with a view to extracting meaningful information. While having more data available may initially appear to be a benefit, as Donalek et al (2014) notes, unless interesting patterns can be drawn from it, these complex data sets are not useful. Considering that the data is not just growing in volume, it is getting more complex with multi-dimensional data sets comprising measurements, spectra, images etc. (Donalek et al., 2014), discovering and analysing any resulting patterns can be more of a challenge.

Another issue is the dimensionality of the data. As data becomes more high-dimensional, more dimensions will need to be visualised effectively because it's more likely that this will result in more interesting patterns being observed in the data (Donalek et al., 2014). The application of VR to finding patterns in data is exemplified by Moran et al. (2015) when they examined how to improve visualisation of data analytics with VR. The goal of such analytics is to discover underlying patterns in the data and display it to the user. As part of their research they mapped tweets to a VR model of the campus of MIT and found doing so made pattern detection easier. These examples illustrate not only that pattern detection is becoming more difficult because of the increase in the volume of data, but also that VR can be used to alleviate this issue. VR can provide more insight into the ability to observe and detect patterns in datasets which is one of the central concepts to data literacy. As data becomes more high-dimensional and more complex, being visually able to more easily detect patterns in these data sets becomes increasingly important for data literacy because as the datasets and dimensionality develop, so should the tools used to explore them.

2.4.2 Understanding

Dale (1969), while an old reference but still relevant, reported that in order to improve learning and understanding skills, human sensory capabilities and motor skills should be actively engaged. VR engages with these senses and skills through the user's vestibular senses of body rotation and balance, sight, hearing, and sense of reality and perception (Jerald, 2015). VR, therefore, should provide some unique benefit in aiding a person's ability to understand by engaging the user more. When using a VR data visualisation, fewer inaccurate findings relating to the data, or insights, are reported from a dataset than when compared to a 2D visualisation (Millais et al., 2018). This is important because the visualisation tool used influences the insights gained from the data and how the data itself is interpreted (Saraiya, 2005).

Another finding of their study was that the VR users reported their performance workload as lower than those using 2D which corresponds to increased feelings of success and satisfaction (Sylaiou, 2010). Albeit on a small scale, this study shows that VR can engage users and therefore potentially improve understanding. However, they also found that, when using the VR visualisation, fewer "deep" insights were discovered in the data than when using the 2D visualisation. "Depth" refers to whether an observation was related to specific data points or to the whole dataset. This suggests that those using the VR visualisation were reporting more accurate insights but not as in-depth as those using the 2D visualisations. This shows that VR users appear to obtain a good understanding of the whole dataset but not the specifics. In terms of data literacy, being able to understand data is crucial because information can't be gained from data that isn't understood and VR is a useful tool that can be used in to aid in a users' understanding of their data.

2.4.3 Visualise

When deciding whether to visualise data in an immersive environment, the type of data being displayed is perhaps the most important factor in terms of their suitability. While data of all types has been displayed in a virtual environment, from charts (Sullivan, 2016) to 3D models (Bergmann, 2017), some forms are better suited to being applied in a VR environment. For example, Sullivan (2016) found that VR charts were more engaging for certain types of information such as looking for an outlier in a dataset. However, this is not to suggest that VR is only useful when looking for an outlier. When handling spatial data, VR is often more beneficial than 2D visualisations. This has been proven in many scenarios, from a class of 5th graders learning how to calculate the volume of 3D objects (Putman and Id-Deen, 2019) to the interpretation of 3D geologic data by geoscientists and geophysicists (Kinsland and Borst, 2015).

This is further evidenced by Bergmann et al.'s (2017) finding that VR is the method of choice when showing realistic impressions of objects or when investigating 3D models. VR is not a useful visualisation tool for every situation. There are occasions where 2D is more effective because of the simplicity of the task or because the task being performed doesn't require depth-heavy information (McIntire et al., 2012). However, VR is very much a visualisation platform. Wagner Filho et al (2018) found that in comparison to desktop-based 2D and 3D visualisations, a Head Mounted Display (HMD)-based immersive 3D visualisation was found to require less effort to find information, required less navigation, and had a greater sense of accuracy and engagement. As such, visualising data in new ways is one of the methods that VR can provide a benefit for data literacy because it will allow for more complex data to be visualised in more intuitive methods.

2.4.4 Explanation

Immersive 3D displays can be used to explain additional abstract information in a way that 2D displays can't. For example, Marriott and Schreiber et al (2018) explain that, when there are more dimensions in the original data, projecting that data onto an additional third dimension will result in less error in that projection. The distances between the points projected onto a 3D space will more accurately represent the original dataset than when projected onto a 2D space where there is a dimension reduction. Take the example of a 3D scatterplot. If it is projected onto a 3D space it would more accurately present the original scatterplot than a 2D representation would because the distances between all the points can't be visualised in a 2D plot. While the time taken to create a VR model may take longer than the time taken to create a 2D model (Akpan and Shanker, 2019), this appears to be down to the tools and techniques used to create it.

This shows that with the correct tools, creating VR models should take the same time as using 2D models. Not only this, but VR models have also been shown to be more effective at presenting the results of the model and communicating them to clients, such as managers or decision-makers, of a simulation project than a 2D display (Akpan and Shanker, 2019). There are areas where 2D displays are more useful, as shown by Marriott and Schreiber et al (2018). They found that while 3D representations show overall structure for datasets such as 3D terrain or networks more clearly, 2D representations are better for accurate data value measurements such as understanding clustering in 2D scatterplots (Marriott and Schreiber et al., 2018). When asked a series of questions based on a provided set of data, the 2D users performed significantly better than the VR users. The VR dataset created by Marriott and Schreiber et al. was "essentially a 3D version of a line graph" (p.13) with one surface plotted as a triangle mesh. This allowed more direct comparisons to be made between the VR and 2D graphs. While they acknowledge a number of improvements that they admit, had they been in the study, would likely have changed their results (Marriott and Schreiber et al., 2018, p.43), these findings support the observation that VR is more adept at explaining spatial data than 2D displays.

Examining the four key concepts, there are occasions where VR is not as useful as other methods, but just as no one tool is useful for every situation, there are areas where VR provides a definite benefit to data literacy. How VR provides benefit to data literacy is by providing a unique benefit to the concepts of visually discovering patterns, understanding, visualisation, and explanation. Donalek et al (2014) and Moran et al (2015) describe how using VR makes discovering visual patterns and insights into data easier, especially with data that is more high-dimensional in nature. It was shown by Millais et al. (2018) that in terms of understanding data, when compared to a 2D visualisation, VR users reported fewer inaccurate insights. Visualising data is perhaps the most obvious benefit that VR can provide to data literacy and it has been shown that when using spatial data that VR is often more beneficial than 2D. When these benefits are taken together, it is clear that there is a potential for VR to provide a lot of benefit to data literacy; this will be further explored in the following section.

2.5 Virtual Reality Application to Data Literacy

This section will explore the studies mentioned in the previous section, with a view to explaining how the results of these studies illustrate the impact of VR on data literacy.

Virtual Reality, by providing a benefit to those concepts, enhances data literacy in turn. When visualising data, there are several factors that need to be considered before determining whether to use a VR visualisation. For example, Sullivan (2016) mentions that for newcomers to VR, 2D charts are faster and more accurate than those in VR due to the user's comfort level with 2D and inexperience with VR. One improvement described by Sullivan is to conduct two sessions with the users, the first of which would be used to better acquaint them with VR and give the users time to get used to the controls. Pattern discovery is enhanced by VR by making it easier to discover patterns in data. Donalek et al. (2014) explain how VR can be used to more easily find patterns from multi-dimensional data by creating a data visualisation inside a virtual world.

This world allowed a user to explore multi-dimensional data by mapping a data set on the X, Y and Z axes as well as giving each point a colour, shape, size and transparency (Donalek, 2014). This allowed for the effective visualisation of a 7-dimensional data point in one location in space in an environment that allowed for the user to walk around all the data points that make up the data set. It also allows for more high-dimensional datasets to be visualised while also enabling patterns or relationships between those high-dimensional points to be discovered by enabling the user to see which points are the same, size, colour, shape etc. In VR a user can "see" multi-dimensional data as a series of points in front of them which allows for multiple ways to map the data to find patterns that may not have been obvious in a previous mapping (Donalek, 2014). Data literacy is benefited from this because the more ways there are of mapping data the greater the potential is for finding more patterns in the data. In the last few years, there have been studies examining how VR can be used to improve understanding in a variety of contexts.

Wijma et al, (2018) have shown that VR can be used to improve understanding and empathy towards people suffering from dementia. They showed that using VR to aid informal caregivers to understand the person with dementia reduces psychological distress caregivers can often experience (Wijma et al., 2018). This study is just one example of how powerful a tool VR can be in aiding understanding. Understanding of data has also been shown to be improved using cave automatic virtual environment (CAVE) immersive displays (Bayyari and Tudoreanu, 2006). A CAVE is a room-sized

VR experience where the user is surrounded by four wall screens; front, right, left and one on the floor. Stereo images are generated by a workstation and are projected onto these screens (Ohno and Kageyama, 2007). When compared against a 2D display in the form of a desktop screen with a hand tracker, a three-wall CAVE, where the three screens were in front, on the right and on the floor, was found to better support the understanding of data (Bayyari and Tudoreanu, 2006); understanding is a core component of literacy as described above.

While this shows the potential of immersive displays, a CAVE and a VR headset are different forms of immersion and indeed have different results. In a comparison between a data visualisation in a VR headset with a 2D visualisation, Millais et al. (2018) found mixed results. They found that while a greater number of accurate findings related to their data set were found by VR users, these insights were not as deep as the 2D users. When considered together, these findings suggest that, while VR can be used to improve understanding, when it comes to datasets, a combination of VR and 2D techniques would provide more benefit to a user than a strictly VR experience. Indeed, in their discussion of potential future work, Millais et al. state as much when they suggest investigating "the impact of embedding 2D visualisations into virtual environments to capitalize on the engaging effects of VR, whilst overcoming possible limitations of 3D representations" (p.6). In order to most effectively improve understanding using VR, the use of 2D aspects inside the visualisation may provide an avenue to overcome some of the drawbacks of an immersive data visualisation. VR is a highly immersive and visual platform.

As illustrated by the Multimedia Cone of Abstraction created by Baukal et al. (2013), VR is the least abstract form of media because of the users' ability to control what they are viewing and move at a pace most comfortable to them and not a pre-set pace. When visualising data, a primary consideration is what form the data is in and what tasks are going to be performed on them. This has been illustrated across a few different studies. One example of when visualising in VR is the method of choice is, as Bergmann (2017) noted, when investigating models or displaying realistic impressions of objects. One of their methods of illustrating this was with a 3D model of a weevil, a type of insect. The weevil could be viewed as either an entire model or as an 'exploded view' that displayed all of its' segments. However, Marriott and Schreiber et al. (2018) found that when performing accurate comparisons of data values, 2D representations are preferable to 3D.

In the conclusions of his work on graph-based visualisations in VR, Sullivan (2016) found that 3D graphs in VR were not intuitive and the users of these graphs were significantly slower and less accurate when compared to users of 2D graphs. While their visualisation of a graph in 3D was not as effective as in 2D, Donalek (2014) was able to create a 3D scatterplot to effectively visualise high-dimensional data sets in VR. These results indicate that there are some forms of data that appear to be more effective when visualised in a VR environment. It has been found that, in a comparative study visualising data centre temperature in VR versus 2D screens, users were able to perceive spatial data better in VR (Nevalainen, 2018). A major consideration for enhancing data literacy with VR is that it should be clear what type of data is being visualised and there should also be an understanding that this affects the potential benefit of any visualisation in a virtual environment.

Having more options to visualise data in turn provides more avenues to attempt to explain it. Explaining data is an essential part of data literacy because, for information to be created and decisions to be made, the data needs to be explained to the eventual end users. VR provides several potential advantages over 2D displays that can be utilised to display data, and therefore explain it, in a more effective manner. Marriott and Schreiber et al. (2018) describe several potential advantages that relate to these novel methods of displaying data. One of these advantages of immersive 3D over 2D that they discuss is using depth to show an additional abstract dimension. Using depth to show an additional abstract dimension describes the ability to use another dimension to reduce error in a multi-dimensional visualisation. The distance between the data points from the original multi-dimensional space are more accurately represented in a 3D space than when it is projected onto a 2D space (Marriott and Schreiber et al., 2018). Therefore, when the visualisation is being explained, the 3D view more accurately represents the underlying dataset and should allow for more accurate insights into the data. These concepts; discovery of patterns, understanding, visualising and explaining are by no means an exhaustive list of the aspects to consider when creating an immersive VR data visualisation. They are, however, factors to bear in mind when recognizing data literacy as important to the VR visualisation. VR can provide a unique benefit to these concepts as discussed earlier and in this way, VR enhances data literacy.

2.6 Conclusion

Data literacy has been defined in many ways by different researchers, as is evidenced by *Table 1*. There is no single standardised definition because there are differing opinions on what constitutes data literacy. As such, a concept centric matrix was necessary in order to find concepts that were common across all the definitions. This revealed eight concepts which were broken into two conceptual groups, where it was perceived that one group, termed "imaginative" could benefit from VR more than the other, "functional" group, could. By considering how these "imaginative" concepts can be improved by VR and by seeking to utilise the benefits VR can provide to them, data literacy can be improved in turn. Data literacy and VR have not been examined together in previous research, as far as the author is aware.

Due to the potential of VR, it is worth examining how VR could be used most effectively to provide the most benefit to data literacy because this will aid in future attempts to create more effective visualisations. It is a relationship that needs to be considered when creating immersive data visualisations because the desired end-result of data literacy is to turn data into information so the user can make an informed decision. VR data visualisations have potential to visualise what is often complex data in a more intuitive manner which makes understanding the data easier. This relationship is an important consideration when future immersive visualisations are created. New tools are needed to more effectively visualise increasingly complex and high-dimensional data. However, there is also a need for an updated understanding of how a users' level of data literacy affects their ability to understand their data and how VR can be used to benefit this.

By understanding data literacy and how it describes the process of turning data into information, it can be seen how VR can be applied to improve data literacy. There are core concepts that affect data literacy which can be improved using VR which have been discussed in this chapter. It is through these concepts that VR provides its benefit to data literacy and is where the creation of future immersive visualisations must focus. By using VR to improve their ability to discover patterns in their data and to understand, visualise and explain their data, data users will be able to improve their data literacy levels which will allow them to improve their understanding of their data and ultimately improve their creation of information.

This chapter has described how these "imaginative" concepts are not only central to data literacy, but they have also been shown to benefit from being applied in a VR context. The creation of future immersive visualisations needs to consider how they can use VR to benefit these "imaginative" concepts and therefore improve the users' data literacy. In so doing, these new visualisations will not just be providing a visualisation for data, but they will provide the added functionality that will aid data users in being able to improve their ability to discover patterns, understand, and visualise data in new ways.

3. An Immersive Data Visualisation Design Process

Abstract

The aim of this chapter is to create a prescriptive process for the development of interactive visualisations in immersive environments, and to test, evaluate and iterate on that process by applying it to a real-world business problem. This process will aid developers of immersive visualisations to reduce trial and error, reduce production time and streamline the process of designing immersive visualisations. The design process will ensure that once development begins, the design of the visualisation will have a foundation that will allow it to enhance the creation of the visualisation itself. Immersive visualisations have been deployed in a wide variety of fields as a potential new tool for data visualisation. However, these applications are often quite unique and specific to an area or domain. As a result of this, the ability to reuse, or refine, the design process can be difficult. The introduction of a prescriptive design process would allow visualisation designers to follow a common process by providing a series of clearly defined steps. This should minimise the amount of trial-and-error that is common in the development of immersive visualisations.

3.1 Introduction

According to the International Data Corporation, an estimate for the amount of data to be created in the world annually forecasts 44 zettabytes in 2020 and 180 zettabytes in 2025 (Press, 2016). As the volume of available data grows, more data visualisation research is necessary so that this increase in volume does not have a significant impact on how that data can be presented. When it comes to creating data visualisations, this increase in volume presents a range of challenges for organisations. For example, in many organisations data visualisation plays a significant role in performance management through data analytics (Kokina et al., 2017).

Data visualisation can be defined as "the graphical display of abstract information for two main purposes: data analysis and communication" (Wang and Perez-Riverol et al., 2015, p.1356). Data visualisation techniques are used in many domains for presenting and understanding to provide an overview of the dataset or to allow searching for patterns and other meaning. For example, they are used in academic studies to communicate the results of the research (Szabo et al., 2019). Goldman et al. (2018) use a variety of data visualisations to showcase their browser-based platform, (which can be found at http://xena.ucsc.edu), for visualising and interpreting cancer genomics data.

The rise in the volume and complexity of data has been so great that traditional methods are inadequate to handle it, therefore new and better visualisations are needed (Agrawal et al., 2015). For them to be as efficient as possible in relation to visualising data, organisations need to use improved visualisation techniques that best suit their specific purpose (Hassan and Elragal, 2017). Donalek et al. (2014) makes the argument that "we cannot really understand or intuitively comprehend anything … that we cannot visualise in some way." (p. 609). As the volume and complexity of data increases, traditional visualisation tools often being inadequate, immersive visualisations are better suited to handle big data and its high complexity and dimensionality (Wang and Wang et al., 2015). Therefore, immersive visualisation as a potential data visualisation and analytics tool becomes more prevalent (Donalek et al., 2014). As discussed in the previous chapter, there are occasions where immersive visualisations provide benefits traditional 2D visualisations are unable to: for example, aiding users in finding a greater number of accurate insights in their data.

Visualising more sophisticated or high-dimensional data can be challenging when more traditional 2D tools are used. This is why data visualisation is likely to benefit from immersive technologies (Andersen et al., 2019). Immersive technologies allow multi-dimensional data to be expressed in what can be a more intuitive manner. Immersive technologies also have the potential to present complex data such as a 3D neural network, which requires a visualisation that goes beyond the capability of 2D visualisations (Marks et al., 2014), in a manner that allows them to navigate it in 3D space. This illustrates how important immersive technologies could become by providing a new tool for the effective visualisation of more complex data.

For the purposes of this chapter, an 'immersive technology' is one that can be found on the Virtuality Continuum (Suh and Prophet, 2018). The Virtuality Continuum is used to describe the range of immersive technologies, with the real world at one end of the spectrum, and a fully immersive 'virtual environment', (or VR), at the other end (Rubio-Tamayo et al., 2017). 'Virtual environments' are defined as "systems relying on high fidelity tracking and displays to facilitate natural perception and interaction within an artificial environment" (Nilsson et al., 2016, p.109). Alternatively, they are defined by Zeng and Richardson (2016) where VR allows the user to control their actions and navigate a virtual world that might simulate the real world (or 'real environments'). The virtual end of the spectrum describes environments that block out the 'real' one and replace it with a fully virtual one (Mann et. al. 2018).

Immersive visualisations provide an avenue for new visualisations that can handle the greater volume of complex data. Unlike more traditional, static data visualisations, they incorporate innovative interfaces, hardware and software applications, and visualisations that incorporate "interaction metaphors and visualisations" (Chandler et. al., 2015, p.2) that are used for understanding data. The interaction methods in these immersive environments allow for more natural interaction with the data (Sicat et al., 2018). Thus, the definition of immersive visualisations that is used in this chapter can be stated as follows:

"Immersive visualisations are data visualisations that are placed within a virtual and artificial environment and allow the user to explore and navigate the dataset within that environment."

The development and use of immersive applications have experienced “rapid growth” and is breaking “into the mass market” (Wang et. al., 2019, p.2). Combined with previous successes with training and educational applications, this will give rise to new tools that will improve “communication, collaboration, and co-creation” (Greenwald and Kulick et. al. 2017, p.2) using immersive visualisations. When it comes to the development of these immersive visualisations however, there is currently no prescriptive process, specific to visualisation, that a developer can follow in order to create an effective solution to adequately visualise their data.

3.2 Development Process

There are several challenges to be faced when it comes to the development and adoption of immersive technologies as a tool for data visualisation. A primary challenge is that there are no methods for the creation of visual analytics tools that make use of the “novel input and output techniques” (Bach et al., 2017, p.1) that are available. The development processes of immersive visualisations are most often specific to each individual use case or domain. Some domains that have seen successful implementations of immersive visualisations include medicine (Zhang et al., 2001), archaeology (Benko et al., 2004), and meteorology (Ziegeler et al., 2001). However, while these implementations of immersive technologies are providing a benefit in these specific areas, the development processes are all unique to the specific domain and visualisation type. From the examples above, Benko et al (2004) needed to visualise data that came in many forms, both 2D and 3D. However, Ziegeler et al. (2001) were visualising highly specific data made up of 3D grid points that depicted the atmosphere.

Creating effective immersive interfaces can also be complex and time consuming (García-Hernández et al., 2016). There are several considerations to be factored in before the visualisation is made. For example, which technology and platform should the visualisation run on and is it necessary for the user to be able to move around the environment. If the user is to move around, how should movement be implemented. The visualisation then needs to be accurate while also being the correct size and dimensions to convey the meaning of the data. Once these, and many other considerations, are dealt with there is still the human effect. How will this affect the user in terms of motion sickness or eye strain? These are difficulties that traditional 2D visualisations don't have to address

In addition, traditional design optimisation processes essentially come down to trial and error (Langnau, 2018). Using a trial and error method to approach a design task is not the optimal design method and is more often used by novices than by more experienced developers and designers, and is linked with a lack of confidence in what the designer is doing (Ahmed et al, 2003). Marriott and Schreiber et al. (2018) also identify the need for a set of development and design guidelines for immersive applications specifically for interaction, collaboration, and design. With no guidelines for developers of immersive visualisations to follow, they must resort to trialling different designs and specifications before deciding on the most suitable one. Having a prescriptive design process to follow would allow the developers to know, before creation of the visualisation begins, the requirements of the visualisation and what is expected from it. This in turn would lead them to be more confident in what they are to do and should minimise the use of the trial and error method.

The prescriptive process that will be outlined in this chapter will allow developers to more efficiently design effective immersive visualisations regardless of graph type or dataset. Immersive technologies, like VR, are "extremely cross-disciplinary" (Jerald, 2015, p. 261) and, as such, a design process for immersive visualisations should come from more than just one discipline. Immersive visualisation design is a field that, as explained by Sicat et al. (2018), "requires knowledge of concepts and technologies from multiple areas of study such as data visualisation and analytics, 3D computer graphics, AR, VR, human-computer interaction, and human factors" (p.715).

Immersive technology development requires several different technologies and individuals with different roles and areas of expertise to create effective environments. The development environment for immersive technology also requires a range of hardware and software requirements. (Berg et. al., 2017). A prescriptive process for the development of immersive visualisations would significantly increase efficiency by streamlining the visualisation design process by outlining what resources are going to be needed before development begins. The design process formulated in this chapter was created as a method of ensuring these factors are sufficiently addressed and that the time taken for design is not delayed by any of them.

The development process created in this chapter will aid developers of immersive visualisations to address the challenges of trial and error and make the designers more confident in their visualisation when choosing a visualisation. It should also help to reduce lengthy production times. The design process will ensure that once production of the visualisation begins, the design will have a more stable foundation to allow the developers of the visualisation to build on.

A research domain that was influential in the development of the immersive visualisation design process was traditional data visualisation design. While it may seem counter-intuitive to study non-immersive visualisations, there are lessons that can be learned from traditional data visualisation design processes that are also applicable to immersive processes. This is because, at their core, data visualisations use any technique that is available to help human perception to identify trends and patterns in what is often complicated data (Kang et al., 2008). There are many prescriptive processes that can be followed during the design of traditional data visualisations. For example, Card (1999) lays out a proposed pipeline for mapping data to a visual format. *Figure 1* below outlines this pipeline.

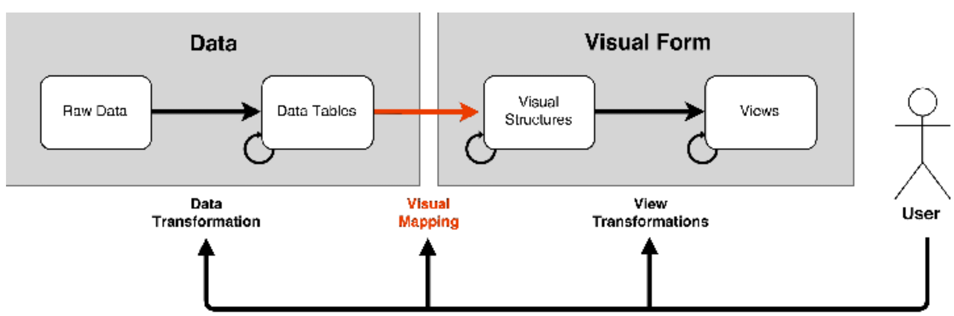


Figure 1. Card et al. (1999) Data to Visual Pipeline

However, in the Card et al. (1999) pipeline for data visualisation, much of the focus is on displaying the data, and user interactions and cognition is left undefined. User interactions, perception and immersion are very important in determining the effectiveness of immersive visualisations (Chandrasekera et. al. 2015). Therefore, this pipeline is unsuitable for immersive visualisation design. While traditional data visualisations processes can perhaps be used as inspiration, they cannot be used as an immersive design process.

3.3 Methodology

An initial analysis of existing literature was conducted to discover the concepts that are important in the design of immersive visualisations. Relevant research papers were discovered by doing a search of key phrases across relevant databases including Google Scholar, ScienceDirect, SSRN, Web of Science, the EBSCO databases, and the AIS electronic library. The key phrases that were searched for were 'immersive visualisations', 'immersive environments', 'data and virtual reality', 'virtual reality design', 'data visualisation development', and 'immersive analytics'. The result of these searches was the return of 122 research papers that encompass 11 core concepts. Research was conducted on the literature surrounding these core concepts, and a Concept Centric Matrix (CCM) was established (*Table 4*) in order to identify the importance of each of the concepts.

The literature review and concept matrix were conducted using the guidelines outlined by Webster et. al. (2002). This CCM informed the creation of the initial iteration of the immersive visualisation design process by highlighting the concepts that are the most relevant to the design of an immersive visualisation. Another research domain that was influential in the creation of the immersive visualisation design process was current software development research and software development lifecycles such as the Agile software development process as described in Highsmith and Cockburn (2001). Agile was an influence because it involves working in iterations. This allows for more feedback from the client and more opportunities to evaluate the process. Aikio et al. (2005), when researching development techniques for visualisation, used an iterative approach so that they could discuss the iterations with the stakeholders.

The research methodology used was based on the Design Science Research (DSR) process (Peffers et al., 2007). This research methodology was applied as it is a methodology that puts a focus on generating design knowledge through building and evaluating ensemble IT artefacts. *Figure 2* below outlines the core guidelines and principles of the DSR methodology.

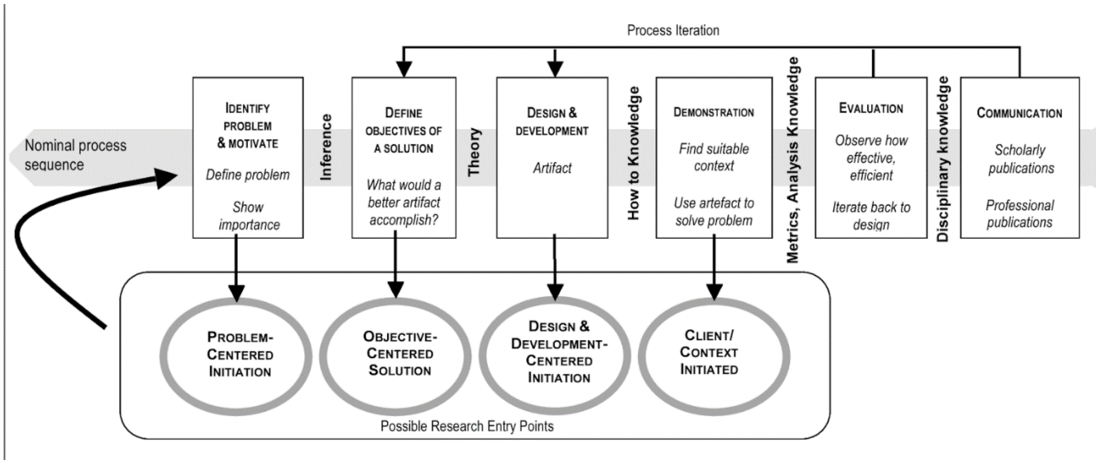


Figure 2. Design Science Research Methodology (Peffers et al. 2007)

Table 3 below lists the stages from the Peffers et al (2007) DSR methodology, a description of each stage, and shows how each stage applied to this research.

Stage	*Description*	*For This Research*
Identify Problem & Motivate	This stage involves identifying, defining and demonstrating the importance of the problem.	This review was carried out in order to define and determine the scope of the research problem and demonstrate its importance. The review revealed the key concepts that were used to inform the creation of the design process.
Define Objectives of a Solution	This stage involves determining what a better artefact would accomplish.	The formulation of a new design process for immersive visualisations.
Design and Development	This stage involves the design and development of the artefact itself.	Using the objectives from the previous stage, in conjunction with knowledge gathered from the CCM, constructing

		the first iteration of the artefact.
Demonstration	In this stage a suitable context is found to use the artefact to solve a problem.	The immersive visualisation design process was implemented to solve a real-world business problem where the objective was to create a prototype visualisation to display financial products and services in a VR environment.
Evaluation	This stage evaluates how effective and efficient the artefact is as well as comparing the desired with the actual outcomes of a solution resulting from the implementation of the artefact.	The evaluation of the effectiveness of the initial iteration was conducted by carrying out a post-mortem of the design process after it was applied to the real-world business problem.
Communication	This stage involves publishing to relevant professional or academic outlets.	This involved communication to stakeholders concerned with the real-world problem as well as presenting the findings in this thesis.

Table 3. Application of DSR Methodology

3.4 Development of the Immersive Visualisation Design Process

After analysing the relevant literature, the following CCM (*Table 4*) was created to illustrate the concepts that are relevant to the development of immersive visualisations and, of these, which were the most important.

Concepts	Level of Immersion	Interaction Requirements	Visualisation Design	Data Analysis	Stakeholder Analysis	User Feedback	Data Transformation	Environment Design	Spatial Requirements	Hardware	Software
Cordeil et al. 2017	x	x	x	x		x	x	x	x	x	x
Helbig et al. 2017		x	x	x	x		x	x	x	x	x
Andersen et al. 2019	x	x	x			x	x	x	x	x	x
Bach et al. 2017	x	x	x	x		x	x	x	x	x	x
Marks et al 2015	x		x				x	x	x	x	x
Wang et al. 2019	x					x		x		x	x
Greenwald et al. 2017	x	x		x	x	x	x	x	x	x	
Berg et al. 2017	x	x	x	x		x	x	x	x	x	x
Olshannikova et al. 2015		x	x	x			x	x		x	x
Campanelli et al. 2015				x	x	x	x	x			x
Fernandez et al. 2008											
Dingsoyr et al. 2012					x	x					x
Yi et al. 2008		x	x	x	x	x	x	x			
Teras et al. 2016	x	x	x	x	x	x	x	x	x		x
Manovich et al. 2011				x			x		x		x
Lee et al. 2012		x	x	x			x	x	x	x	x
Keim et al. 2008		x	x	x	x	x	x				x
Thomas et al. 2004		x	x	x			x	x			
Cliquet et al. 2017	x	x	x	x		x	x	x	x	x	x
Dünser et al. 2007		x				x		x			
Brath et al. 1997		x	x	x			x				
Bunte et al. 2012			x	x			x				
Rubio-Tamayo et al 2018	x		x	x	x			x	x		x
Jerald 2015	x	x	x		x	x		x	x	x	x
Djorgovski et al. 2018	x	x	x	x							
Kandel et al 2012		x	x	x			x				x

Table 4. Immersive Visualisation Development Concept Centric Matrix

Concept	*Concept Explained*	*Iteration One Design Process Step*
Stakeholder Analysis	An evaluation to understand stakeholders and their relevance to a project (Brugha et al., 2000).	User Analysis
Data Analysis	Representing, displaying and studying variation in data (Ramsay, 2004).	Data Analysis
Data Transformation	A sequence of operations that transform a set of input data to a set of output data (Dingman et al., 2004).	
Spatial Requirements	In "reality" it refers to the physical space taken up (Buijs et al., 2011). For this chapter it will refer to the virtual space in the environment that the visualisation will need.	Requirements
Hardware	Devices that can store and perform operations on data or produce outputs (Van Der Meulen, 2012).	
Software	The development platform used such as Unity 3D (Wang and Mao et al., 2010).	
Level of Immersion	The ability for the visualisation and the technology to create a "vivid illusion of reality to the senses of a human participant" (Cordeil et al., 2017).	
Visualisation Design	Good visualisation design is a visualisation that is robust, accessible and elegant (Kirk, 2016).	Environment Design
Environment Design	The design of landscapes and natural surroundings to be aesthetically enjoyable (Study.com, 2019).	
Interaction Requirements	The tools that a user needs to make use of the environment they are in. These tools need to be intuitive, easy to use and best facilitate the user in their data analytics tasks (Helbig et al., 2017).	Interaction Design
User Feedback	Feedback solicited from users of a system (Belhajjame et al., 2011).	Evaluation

Table 5. Relationship of the concepts to the design process

11 core concepts were identified and presented in the CCM. As can be seen from concepts such as Environment Design, Visualisation Design, and Interaction

Requirements, many of those that need to be considered in the development of immersive visualisations are heavily design focused. Design decisions are primarily based on the data that needs to be visualised. The heavy focus on design in much of the literature inspired and influenced the first iteration of the immersive visualisation design process. There are several concepts, coming from the CCM, that need to be considered when designing a process for the creation of immersive visualisations.

The following table explains the concepts from the CCM and how they are relevant to the first iteration of the prescriptive design process shown in *Figure 3*. The goal here is to create a development process based on the key concepts identified from the literature.

There are concepts in *Table 5* that would not be major considerations when designing traditional visualisations. For example, 'Hardware' such as headsets, controllers, base tracking stations etc. and 'Software' like Unity 3D and Unreal Engine (Jacobson and Lewis, 2005) are considerations that are necessary to adequately immerse the user and faithfully represent the data in an immersive, virtual environment. 'Interaction Requirements' is another concept from the literature that must be carefully considered when designing data visualisations (Lee et al., 2012). However, many interactive tasks that use visualised data are inefficient and unintuitive when using traditional methods (Moran et al. 2015). As a result, there is a need for more interactive data analysis instruments.

Figure 3 below shows the first iteration of the immersive data visualisation process that was created based on the core concepts identified. While this process takes inspiration from earlier models of data visualisation, it also combines the important concepts of immersive data visualisation design. Following the DSR process outlined by Peffers et al. (2007), the relevant concepts shown in *Table 5* were represented in the immersive visualisation design process as it appears in *Figure 3*.

The next stage was to test the process. This was achieved by applying it to the real-world problem of creating a prototype immersive visualisation to display a large number of financial products and services.

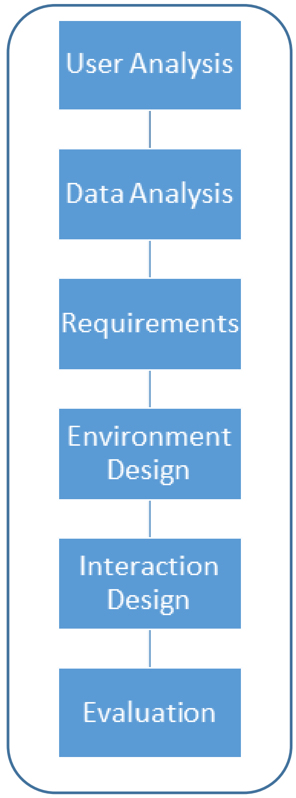


Figure 3. Immersive Data Visualisation Design Process – Initial Iteration

Table 6 below explains each of the steps from the initial iteration of the design process with example suggestions of considerations that could help maximise the effectiveness of the visualisation. While the initial process steps, described in *Figure 3* above, is the first iteration (as per Design Science Research) of the immersive visualisation development process, it required further refinement. This was done through the work on the real-world development project. During each of the process stages, discussions took place with the client and these discussions were then used to refine the process. These refinements are based on enquiries made during the development process. These enquiries represent areas where the process steps did not fully capture all the necessary details for the development of the real-world project. The enquiries, and the stage they applied to, are detailed in *Table 6* below,

For example, in the 'Requirements' stage: 'What are the end goals that the visualisation aims to achieve?' These questions were important to the development of the second iteration as they raised issues to the client that needed to be considered as part of that step. The second iteration retained and refined the steps from the first iteration and two new stages were added: 'Iteration' and 'Feedback'. The second iteration can be seen in

Figure 4. These stages were added as it became clear that the process could not have a definite “Start” and “End” point because the customer will always have feedback and the designers will notice flaws that need to be fixed. Therefore, a more cyclical process was developed in order to account for this.

Iteration One Design Process Step	*Process Step Explained*	*Considerations for the Step*
User Analysis	Obtaining a comprehensive understanding of the main stakeholder operators of the immersive visualisation, as well as any other users and stakeholders that will be influenced by the design of the visualisation.	‘How complex can the visualisation be in terms of the available interactions?’ ‘What level of complexity can the user understand in terms of the formation of the data points?’
Data Analysis	Ability to identify the sources, formats, and accuracy of the data that need to be considered when designing the immersive data visualisation.	‘How is it decided what data is to be included?’ ‘Is the most appropriate analysis technique being used?’
Requirements	Identifying the objectives as well as any ethical or legal obligations that need to be considered when designing the visualisation of the immersive visualisation.	‘What are the end goals that the visualisation aims to achieve?’ ‘What is the output of the various interactions?’

		'What are the learning outcomes that come from using the visualisation?'
Environment Design	The design process for all of the objects that will be present and that the user can interact with.	'How will the necessary data be presented to the user?' 'Is the environment intuitive to experience before interaction?'
Interaction Design	The design of the various interaction techniques that will be implemented in the immersive visualisation.	'Are there any negative aspects that arise from certain interactions, for example, motion sickness and how much of an impact will it make?'
Evaluation	The assessment of the current version of the immersive visualisation design.	'How are all of the various stakeholders affected by this immersive visualisation?' 'What are the learning outcomes that resulted from the design of this visualisation?'
Iteration	Fixing any issues that have arisen as a result of the evaluation phase.	

Table 6. Iteration One Design Process Enquiries

The enquiries listed above are only a sample of the improvements made to the initial iteration, the following section will go into more detail on the improvements that were made to improve the process.

3.5 Iteration of the Immersive Visualisation Design Process

After the immersive visualisation design process was demonstrated, in following the DSR process it then had to be evaluated (Peffers et. al. 2007). For this immersive visualisation, the clients were the primary users and they provided evaluation through their feedback of the immersive visualisation. The above immersive visualisation design process (*Figure 3*) was used as a method of designing the immersive visualisation and, upon examining their evaluation and feedback, there were several issues and inefficiencies identified with the process.

One issue with the process that was identified was that the ‘Environment Design’ and ‘Interaction Design’ stages were very inefficient. They were inefficient because the client didn’t know the capabilities of the designers and the client wasn’t sure what they wanted. As a result, prototyping in the ‘Environment Design’ stage was largely created with 2D methods because the designers wanted to avoid spending resources on an incorrect visualisation. However, this ‘Environment Design’ issue created a compounding problem for the ‘Interaction Design’ stage because the interactions the client wanted couldn’t be developed until an environment was agreed on. This led to a trial and error approach where visualisation designs and interaction techniques were created but the client couldn’t “experience” them and so they would be discarded. Until a 3D showcase of the environment was used, progress on this stage was slow.

As designing an immersive environment can be quite difficult and time consuming (García-Hernández et al., 2016), this issue increased the time spent on the entire design process for much longer than was initially intended. The observation made was that there needed to be a better protocol in place when it came to the design of the environment in the immersive visualisation in order to increase efficiency and remove any form of trial and error.

The solution to this issue was a change to the visualisation design process that added a sub-iteration cycle within the ‘Environment Design’ and ‘Interaction Design’ stages of the process, as shown in *Figure 4*. The aim of this change is to enable immersive visualisation developers to quickly identify and fix any issues in the environment design before moving on to the next stage of the process. It became clear that the design of the immersive visualisation was taking too much time because user feedback was not being implemented until the end of the process. Jerald (2015) suggests several design approaches immersive technology developers can use, two of which are: Human-Centred Design and Continuous Discovery Through Iteration. However, both of these approaches require that feedback be received early and often so the experience is constantly improving, and progress is being made. This is similar to an Agile approach where reviews occur more often than in traditional software development; it is even explicitly stated that traditional methods are “largely useless in VR” (Jerald, 2015, p.374).

It can be difficult and time consuming to make changes late in the process than doing so nearer the start. As a result, the last amendment to the design process was to implement continuous user feedback across all of the design stages of the process. This would quickly identify any issues that arose in a stage before moving on to the next stage. The second iteration of the immersive visualisation design process is shown in *Figure 4* below.

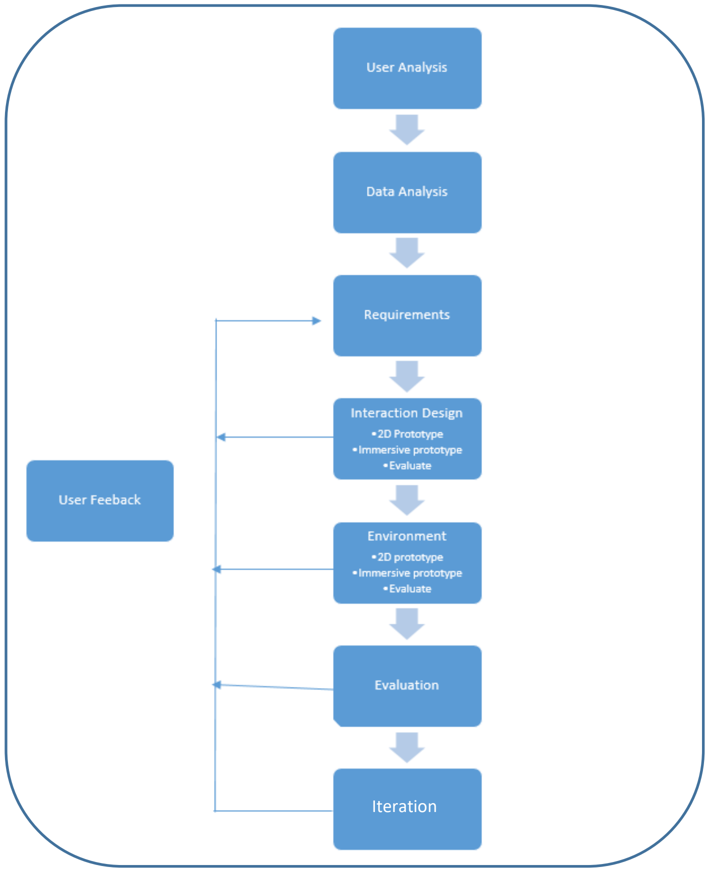


Figure 4. Immersive Visualisation Design Process – Final Iteration

3.6 Conclusion

There has been a recent increase both in interest and research into practical applications of immersive technologies. This has, in turn, increased the potential for immersive data visualisations to be implemented on a widespread basis as a means of effectively visualising data, enhancing user cognition, and enabling efficient data analysis and discovery. The immersive data visualisation design process, presented in this chapter, aims to help developers of new immersive visualisations and prototypes follow a prescriptive method when designing an accurate visualisation that is effective in its purpose and maintains the integrity of the original data. By following this process, developers will not have to go through an extensive trial and error process when creating an immersive visualisation.

The process created through this chapter's research can help designers of immersive visualisations because it ensures constant evaluation of the design and supports frequent discussion with the client. It also ensures that feedback is frequently given and incorporated into later iterations of the visualisation. However, it also includes aspects that are specific to immersive visualisations. For example, the inclusion of an immersive prototype in the final iteration. This was included because it was found, from the application of this process to a real-world problem, that if the client could not see the immersive prototype of the visualisation it was difficult to get meaningful feedback to progress the visualisation.

Having no process to follow can lead to time being wasted determining where and how to start creating an immersive visualisation. Even then, once the process has begun, it was found to be difficult to know how to know what the visualisation should look like and exactly what the client needs. However, through the use of this process, there are steps to follow that show how these problems can be solved. Through frequent displays of immersive prototypes and feedback from the client, among other steps, it is easier to understand and faster to develop what is needed from the visualisation and how this can be achieved.

4. Investigating the Sensory Conflict Theory in Virtual Reality Data Visualisations

Abstract

The aim of this chapter is to examine if the Sensory Conflict Theory is the best explanation of motion sickness for VR data visualisations, as it is for other VR experiences, and how severe the effects could be. Motion sickness is an adverse effect that is experienced by many VR users and is a serious consideration when creating VR data visualisations. According to the Sensory Conflict Theory, it is brought about when there is a mismatch between what the user perceives and what they feel. For example, if the user perceives in a VR headset that they are moving forward when, in reality, they are standing still, then motion sickness can result. Often, the experience of navigating or moving around in VR can result in motion sickness being experienced by the user. Because of this, one of the challenges of creating a VR data visualisation is finding the navigation condition with the least adverse effect on the user in terms of motion sickness. Another issue for VR data visualisations is whether, as mentioned above, the Sensory Conflict Theory adequately explains motion sickness or if there are other potential explanations. While the Sensory Conflict Theory is the most widely accepted theory explaining how motion sickness occurs, there are other potential explanations that could be the cause. In order to examine this issue for VR data visualisations, and how severe the motion sickness effects are, two data visualisations were created with two different navigation conditions. The first navigation condition is a “glide” style navigation where the participant can move forward or backward in the direction they are facing in the VR data visualisation. The second condition is a teleport condition where the participant points to an area on the ground they wish to teleport to. According to Sensory conflict theory, the glide condition should cause motion sickness because the user will perceive motion. Conversely, the teleport condition, where the user does not perceive motion, should not. This chapter will examine whether the Sensory Conflict Theory explains motion sickness in VR data visualisations and which of the two navigation conditions is less taxing on the user of the VR data visualisation.

4.1 Introduction

Motion sickness is a pervasive issue in Virtual Reality (VR) and has been reported on in many different studies such as Munafo (2017) and Golding (2015). The widely accepted theory of the cause of motion sickness is the Sensory Conflict Theory (Zhang, 2016). This theory states that motion sickness occurs when a users' visual and vestibular signals don't match (Jerald, 2015). A person's vestibular system is their sense of self-motion and balance (Dieterich, 2015). When the signals coming from the vestibular system don't align with what they visually see, then motion sickness can result. This is the most widely accepted theory for the cause of motion sickness; but it is not the only theory. The question addressed in this research (Research Question 3 in this thesis) is how much of an effect does motion sickness have in VR data visualisations and what is the potential reason behind what causes it. Unlike VR games which have been designed to limit motion sickness (Robinson, 2015), the designs of VR data visualisations do not consider motion sickness. While the design process from the previous chapter improves upon the method of creating a VR data visualisation, the role of motion sickness in the process was not a major factor in it. While some studies will mention the hardware requirements needed (Theart et al., 2017), none mention the motion sickness impact on their VR data visualisation.

VR is becoming a more important visualisation tool because current 2D tools are inadequate to handle the growing amount of increasingly complex data (Wang et al., 2015). Therefore, the need for newer tools to visualise this data has become increasingly important. As examined in Chapter 2, the use of VR as a potential new visualisation tool has several potential benefits. However, by implementing VR visualisations the effect of motion sickness becomes a new issue for data visualisation because it does not impact 2D visualisations. While VR headsets have been growing in popularity, they still cause motion sickness (Munafo, 2017; Palmisano, 2017) and as a result of this, motion sickness could also occur in VR data visualisations. However, because this is a potentially new problem for data visualisations, the reason why motion sickness occurs in them has yet to be examined.

The layout of this chapter is as follows. The next section offers an explanation for motion sickness and describes the various theories which explain its causes. In addition, the other terms that have been used to refer to motion sickness are discussed to provide a background to motion sickness. This will provide potential alternatives to the Sensory Conflict Theory to explain why motion sickness occurs in VR data visualisations. The experiment itself, where two navigation conditions were tested to determine a potential reason behind motion sickness in VR data visualisations, is then described followed by an analysis of the results that were obtained.

4.2 Motion Sickness

Motion sickness is one of the main problems associated with VR technologies because it can not only disrupt a person's sense of presence in the virtual environment, but it can also adversely affect a person's health. It has been described as "a feeling of unwellness caused by motion, especially during traveling and virtual reality immersion"; the symptoms range from fatigue to nausea and vomiting (Zhang et al., 2016, p.15). There have been multiple classifications of motion sickness. For example, Bertolini and Straumann (2016) have defined it as "a common disturbance occurring in healthy people as a physiological response to exposure in motion stimuli that are unexpected on the basis of previous experience" (p.1). This definition clarifies that it's not only expected motion, but it can also be unexpected motion that causes sickness.

While the following motion sickness theories that are to be explained in this section apply to VR in general, there are different "experiences" that can be made for a VR headset, each of which handle motion sickness in different ways.

What is meant by this can be explained using three examples of a "VR experience": a 360-degree video, a VR game, and a VR data visualisation. A 360-degree video in a Head Mounted Display is one where the user can move their head in different directions to view different sections of a spherical video (Corbillon et al., 2017) while their actual position remains the same. Corbillon et al. (2017) did not consider how motion sickness could affect the user because of the idea that "no motion equals no motion sickness" (Robinson, 2015). VR games are potentially the most widely known examples of VR (Carbotte, 2018). However, motion sickness is a major concern for these games and much consideration is given to how it can be minimised (Robinson, 2015). On the other hand, VR data visualisations are often used for a specific purpose such as sensor data visualisation (Baltabayev et al., 2018) and it is often not known whether motion sickness was experienced by the users. Other studies, such as Theart et al. (2017) mention the minimum 60 fps frame rate that is needed from the VR hardware to avoid motion sickness but do not mention the effect, if any, of motion sickness in the VR data visualisation they created. Therefore, motion sickness is effectively not being taken into consideration in VR data visualisations even though it has a potential negative impact.

While it may be the most common term, motion sickness is not the only term that has been used to describe illness arising from an experience with a virtual environment. Because these terms can often be similar to motion sickness, a clarification is needed so that it is clear what is meant by motion sickness in this chapter. Examples of other terms that have been used in the literature are simulator sickness, cyber-sickness and Visually Induced Motion Sickness (VIMS) (Cohen, 2016; Gavgani et al., 2018; Cobb et al., 1999; Kennedy et al., 2010). VIMS is similar to motion sickness with the difference being that physical movement is usually absent or limited (Keshavarz, 2015) and sickness results from what the user visually perceives. It has been used as an umbrella term for subcategories such as cyber-sickness when it occurs in virtual environments, gaming sickness during video games, and simulator sickness when in flight or driving simulators (McCauley and Sharkey, 1992; Merhi et al, 2007; Brooks et al., 2010).

Even though VIMS can be considered the umbrella term when there is no physical movement, this is not a stringent rule because simulators can still provide physical movement which can cause sickness. It has been found that cyber-sickness and "classic" motion sickness (resulting from being in a moving car for example) are clinically identical (Gavgani et al., 2018). Of the Nausea-Oculomotor-Disorientation (N-O-D) symptoms of motion sickness taken from the Simulator Sickness Questionnaire (SSQ) (Kennedy and Lilienthal, 1993), the only difference between motion sickness and VIMS is that Oculomotor symptoms (problems relating to the eyes) are more prominent in VIMS (Stanney and Kennedy, 1997) but is otherwise the same as motion sickness. Therefore, for the purposes of this chapter in relation to VR data visualisations, simulator sickness, cyber-sickness, and VIMS will be considered effectively the same as motion sickness.

There have been several reviews of motion sickness in VR and its effects on VR users. However, there has yet to be an examination of whether it specifically occurs in VR data visualisations, or the potential reasons why it may occur. If it does occur, there is also the question as to how severe it could be for the users of VR data visualisations.

An explanation for why motion sickness occurs is provided by the evolutionary theory (Treisman, 1977). This theory states that the reason for experiencing motion sickness is that, if a person gets conflicting information from their senses, something has gone wrong with their perception and there may be toxins in the body. The body has developed protection methods such as vomiting and sweating to eject any perceived toxins from the body. While the evolutionary theory explains why motion sickness occurs, there is no definite answer to the question of what causes motion sickness. There have been several theories proposed as to what causes motion sickness and, while some are more popular than others, it is worth examining different reasons to gain a better appreciation of why motion sickness could occur in VR data visualisations. The primary theories considered in this chapter are the eye movement, sensory conflict and postural instability theories (Brooks et al., 2010) as well as the rest frame hypothesis (Jerald, 2015) and vection.

The Sensory Conflict Theory is the most widely accepted explanation of the cause of motion sickness (Harm, 2002). It states that motion sickness results from information coming from the different senses not being compatible with each other and not matching our expectations. The two primary senses involved are the visual and vestibular systems. The vestibular system is our sense of balance and self-motion which is primarily detected by the otolith organs in the inner ear. In VR, for example, if the user sees that they are moving but doesn’t feel it (i.e. their visual and vestibular cues don’t match) this can result in motion sickness. However, in their research into a comparison between VR and Augmented Reality (AR) in terms of safety, Pettijohn et al. (2019) found that “the mismatch between visual and vestibular motion does not lead to increased sickness or performance reductions beyond those of motion alone” (p.3), which implies that it may not be the case that the Sensory Conflict Theory explains the causes of motion sickness and that motion in and of itself causes sickness. So, while there is not universal agreement to the validity of the Sensory Conflict Theory, it is the most widely accepted theory. It must be acknowledged, though, that there are occasions where it does not fully explain motion sickness, and the question remains if it explains motion sickness specifically in VR visualisations.

The eye movement theory states that it is the unnatural eye movement, required to keep an image stable on the retina, that causes motion sickness. When an image doesn't move as expected, a conflict arises between what the eyes expect and what actually occurs. This causes the eyes to move differently than they would in the real world, which results in motion sickness (Jerald, 2015). In terms of explaining motion sickness occurring in VR data visualisations, this could be a potential explanation. Depending on the navigation condition, any movement by the user may not be a completely "natural" movement and therefore the image on the retina will not be what was expected, leading to motion sickness.

Postural instability is being unable to control the posture of the body (Stoffregen et al., 2000). Postural instability theory provides a prediction as to when motion sickness may occur as postural instability precedes motion sickness. Riccio and Stoffregen (1991) suggest that motion sickness results when a strategy for maintaining postural stability hasn't yet been learned and that sickness results when there is no strategy for maintaining balance. They argue that the longer and more unstable one is, the worse the sickness will be. VR users can also learn how to control their posture over time (Jerald, 2015). Because this theory is only a predictor of motion sickness, and the fact that it can be learned, means it could be a factor for new users of VR data visualisations but it is unlikely to be the best explanation for motion sickness for all users.

Another theory about the cause of motion sickness is called the rest frame hypothesis theory (Prothero and Parker, 2003). This suggests that there is a "rest frame" which is a part of a scene that the viewer considers stationary and which the movement of other objects, and oneself, is judged against. If new sensory cues don't match what is expected of the scene and the rest frame does not appear stationary, motion sickness can result. For VR data visualisations, this could also be a potential reason for motion sickness. However, it is a more complex theory when compared to the others, as described by Prothero and Parker (2003) and the user of the visualisation may not know, for definite, what the “rest frame” of the visualisation for them would be.

Another potential cause of motion sickness is what’s known as vection. Used to refer to the sensation of self-motion induced in viewing optical flow patterns, vection can be induced when viewing representations of motion in the linear or rotational aspects of the body (Hettinger et al., 1990). In simple terms, it is the sensation of movement of the body produced by visual simulation alone (Barnes, 2019). The real-life example to explain this is when on a stationary train, seeing a neighbouring train moving gives the illusion that one’s own train is really moving. However, it is still the matter of some debate as to whether vection is really needed to cause visually induced motion sickness (Keshavarz et al., 2015) and therefore is considered as unlikely to be the reason behind motion sickness occurring in VR data visualisations.

4.3 Methodology

After reviewing various studies on VR and motion sickness, a research question emerged as to how severe motion sickness in a VR data visualisation can be and what is the most likely reason it may occur (Research Question 3 in this thesis). In order to identify relevant research in the area of motion sickness in VR data visualisations and what the potential reasons for it may be, a systematic literature review was carried out. This literature review followed the process as laid out in Webster and Watson (2002). Papers were searched using the terms “virtual reality and motion sickness”, “virtual reality and simulator sickness” as well as “virtual reality navigation methods” “virtual reality navigation motion sickness” and “immersive visualisation motion sickness” on Google Scholar as well as the EBSCO database and the AIS electronic library. These searches resulted in a total of 174 papers, 80 of which were deemed irrelevant from reading their title and the abstract. From reading the remaining papers it was discovered 40 papers were relevant to this research.

To answer the research question (Research Question 3) an experiment was carried out to measure the level of motion sickness experienced by the participants when given different navigation conditions and to examine potential reasons for why motion sickness occurs in the visualisations. This involved giving two groups of participants a

VR data visualisation with different navigation conditions. As stated previously, the Sensory Conflict Theory is most likely to be the reason for motion sickness in VR data visualisations but, in order to determine if this is correct, two navigation conditions were used in the test: one navigation condition that the theory suggests will cause motion sickness and one navigation condition that should not. If the results are in line with the theory (i.e. the condition that adheres to the predictions of the Sensory Conflict Theory has worse reports of motion sickness), then this is most likely to be the reason for motion sickness in VR data visualisations.

To choose the navigation conditions that would test the Sensory Conflict Theory for VR data visualisations, the two navigation conditions needed to be similar so that a more direct comparison of the results can be made. For example, the use of more novel navigation conditions from existing research such as a walking-in-place solution (Tregillus and Folmer, 2016) or flying with virtual wings (Yoon et al., 2018) would not allow for a comparison of any reports of motion sickness because they are not similar conditions and therefore would not be a like-for-like comparison. For the purposes of this research, the two navigation conditions that were implemented were a “glide” condition and a “teleport” condition.

The technology used for the experiments was the HTC Vive with a Vive controller connected to a Windows 10 PC with an intel Core i7 processor with 16 GB of RAM. The HTC Vive has 110-degree field of view with a 90hz refresh rate and a resolution of 1080 * 1200 pixels per eye with a dual AMOLED 3.6” diagonal screen. Using the “glide” condition, the participant is able to move forward or backward in the direction they were facing by pressing the corresponding direction on the trackpad on the HTC Vive controller. In the teleport condition, the participant used a laser pointer to point to an area on the ground of the VR visualisation to teleport to. To initiate the teleport function, the trigger on the Vive controller had to be pressed. Once initiated, the screen would briefly fade from the environment to completely black and back to the environment with the participant reappearing in the new location. These conditions were chosen so that the only difference between the two was whether the participant could watch themselves move to another position (“glide” condition) in the visualisation or not (teleport condition). This ensured the only difference between the visualisations was that the Sensory Conflict Theory predicts different results: one causing motion sickness and one not.

All the participants (n=8) were researchers in the Advanced Technology Centre in University College Cork and were chosen because they had a wide range of experience with 3D interfaces and therefore would provide more diverse reports on the VR data visualisation. As explained by McAvoy (2006), it is their expert knowledge of the area that makes the participants key informants.

There are several ways of visualising data in VR and VR allows for the visualisation of more high-dimensional and complex data (Donalek et al., 2014). However, for the purposes of this chapter it was decided to use a relatively simple dataset in order to establish how much of a factor motion sickness has on even a simple data visualisation. Therefore, it was decided to use a 3D scatterplot of the publicly available Iris dataset. This data set was used because it was readily available and easily converted to a 3D scatterplot which lends itself well to being visualised in VR environments. It has also been used as the dataset in other research, for example Galili (2015) used it for comparing clustering algorithms. To create the visualisation, the Unity 3D programme was used with a csv of the Iris dataset to create the scatterplot.

The Iris data set consists of three species of the iris flower where each species has 50 instances, therefore giving a total of 150 rows. The dataset has 4 numerical columns measuring the length and width, in cm, of the petal and sepal parts of the flower. A fifth column provides the names of the species which are: “Iris Setosa”, “Iris Versicolour” and “Iris Virginica”. However, in order to create a 3D scatterplot of this data, the “petal length” and “species name” column was excluded. Therefore, the three columns used for each axis were the “sepal length”, “sepal width” and “petal width” columns. In order to make the data points as clear as possible from each other, each point was given a unique colour depending on its X, Y, Z position in the VR environment. In this way, the participants can still make the distinction between points that may be positioned close together.

Each participant was put into one of two groups: one group experienced the “glide” condition first and the other group experienced the teleport condition first. The participants were given time to acquaint themselves with the environment and were then asked to carry out a number of tasks. To minimize the effect of the order of the conditions, a Latin-square design was used. This design is as follows. There are two groups "A" and "B" and the two conditions "glide" and "teleport". Group "A" experience "glide" first followed by "teleport", while group "B" experience "teleport" first followed by "glide".

While there are different questionnaires used to measure motion sickness, as documented by Zhang et al. (2016), the Simulator Sickness Questionnaire (Kennedy and Lilienthal, 1993) was used because it has been used in many previous studies (e.g. Fernandes and Feiner, 2016; Singla et al., 2017 and listed by Kim et al. (2018)) as a way to subjectively measure how ill a participant feels after having been in a virtual environment. While the Simulator Sickness Questionnaire (SSQ) is not a recently developed method of evaluating motion sickness, a re-evaluation performed by Balk et al. (2013) concludes that it is a still relevant method of evaluation.

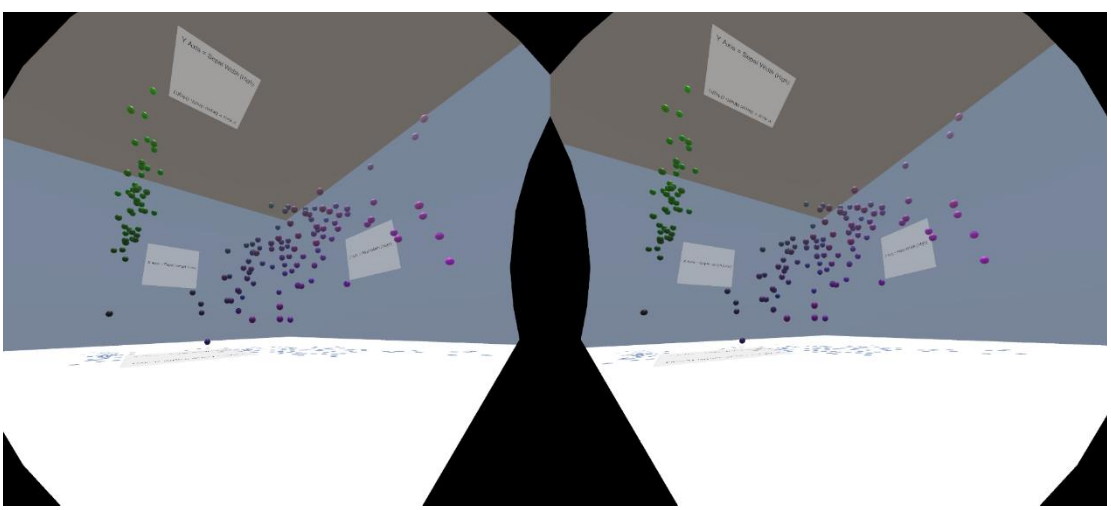
Each group experienced their first navigation condition after which participants were given a break where they filled in the SSQ for the first condition. They were then given the second navigation condition and asked to fill out another SSQ. The participants evaluated motion sickness using a Likert Scale (0=none, 1=slight, 2=moderate, 3=severe). The SSQ consists of 16 different items which are grouped into 3 categories: Nausea, Oculomotor, and Disorientation. Each item is scored between 0 and 3 according to the scale above. The SSQ yields 4 results: one for each of the 3 categories and a total score. Each category is assigned a weight to be used when calculating the results.

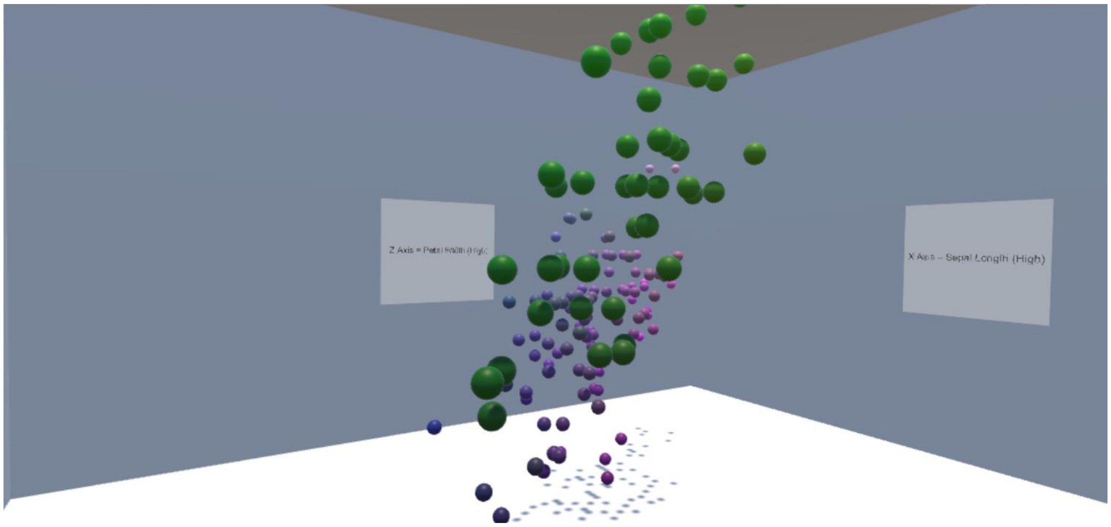
There are two ways the SSQ can be used: one where the questionnaire is administered both before and after immersion in the VR environment; and the other where it is only provided after immersion. There are advantages and disadvantages to both approaches but in this study it was decided to only administer the questionnaire after each test because providing the SSQ beforehand, as well as after, has been found to make the participants more aware of, or sensitive to, any sickness during the test which could skew the results (Young et al., 2007). It is also recommended to use the SSQ only after the session and not beforehand because doing so renders the difference scores unreliable (Johnson, 2005).

4.4 Experimentation

All of the participants reported in the SSQ that they had at least some experience navigating 3D space using a controller. All participants experienced both navigation conditions and all spent the same amount of time in each environment to ensure length of exposure was the same across all conditions. One group experienced the “glide” condition followed by the teleportation condition while the other group experienced the teleportation condition first followed by the “glide” condition. The reason for this was to exclude the possibility that the condition experienced first could result in worse reports of motion sickness than the second condition due to the participant being unfamiliar with the environment. Before conducting the tasks, participants were told to take a minute or two to get used to the environment as well as the controls. The environment in both conditions was the same.

The environment consisted of a room where each wall, as well as the floor and the ceiling, were labelled according to the axis they represented. For example, the “East” and “West” walls represented the X-axis of the 3D scatterplot, the “North” and “South” walls represented the Z-axis while the floor and ceiling represented the Y-axis. Lower X-axis values were closer to the “West” wall while higher X-axis values were closer to the “East” wall. Similarly, while lower Z-axis values were closer to the “North” wall, lower Y-axis values were closer to the floor. In this way, the participants could “see” from these labels what the data represented. The tasks required were to find the maximum and minimum points on each axis and to find any outliers in the data.





Figures 5,6. VR 3D Scatterplot

Figures 5 and *6* above illustrate the visualisation that was created for the experiment. They show the 3D scatterplot as well as the floor (white), ceiling (grey) and walls (blue) of the visualisation. The light grey panels with text on them explain which axis relates to that surface and whether it is the high or low end of the axis. For example, data points that are closer to the ceiling have higher "Sepal Width" (Y Axis) values and data points closer to the floor have lower "Sepal Width" values. The wall on the right-hand side of the visualisation in *Figure 5* is the high end of the "Petal Width" values (Z Axis) while the wall on the left-hand side of *Figure 5* represents the low end of the "Sepal Length" values (X Axis). *Figure 6* shows that the purple data points have higher X and Z axis values because they are closer to those respective walls than the green data points. The wall on the left-hand side of *Figure 6* is the high end of the Z Axis, while the wall on the right-hand side of *Figure 6* represents the high end of the X Axis.

Because all the columns from the Iris dataset were not included, gaining a complete understanding of the dataset would not have been possible. Therefore, the tasks to be carried out require an understanding not of the entire Iris dataset, but rather only of the 3D scatterplot they would be seeing. The tasks also required the participants to move around the environment so that the navigation condition is sufficiently used. In both conditions, the Vive controller was used to enable navigation around the environment.

The Simulator Sickness Questionnaire (SSQ) was given out to each participant twice during the experiment. The first time was after the first condition was experienced, and the second questionnaire was given on completion of the second condition. This ensured that the levels of motion sickness experienced could be separated between the two conditions and the results would not be conflated. This would also allow for comparisons between the two groups to determine what effect, if any, the order of the conditions had on the effects of motion sickness.

4.5 Results

The participants had an average age of 23.5 years (standard deviation = 0.5 years), and all reported they spend at least 40 hours on a computer in an average week. Familiarity with systems such as VR that did not use controls such as keyboard, mouse or touchscreens were more varied with responses ranging from once to over 20 times across the participants. These responses suggest that the participants are familiar with computers but have varying degrees of experience with 3D interfaces.

	Total Teleport Reports				Total Glide Reports			
	None	Slight	Moderate	Severe	None	Slight	Moderate	Severe
General Discomfort	62.5%	37.5%			37.5%	37.5%	25.0%	
Fatigue	75.0%	25.0%			50.0%	25.0%	25.0%	
Headache	87.5%		12.5%		62.5%	25.0%		12.5%
Eye Strain	62.5%	25.0%	12.5%		25.0%	62.5%		12.5%
DiffFocusing	62.5%	37.5%			25.0%	50.0%	12.5%	
Salivation	87.5%	12.5%			87.5%		12.5%	
Sweating	87.5%	12.5%			87.5%	12.5%		
Nausea	87.5%	12.5%			50.0%	50.0%		
Concentrating	62.5%	37.5%			62.5%	12.5%	12.5%	
Sinus Pressure	75.0%	25.0%			75.0%		25.0%	
Blurred Vision	50.0%	37.5%	12.5%		37.5%	62.5%		
Dizzy Eyes Open	62.5%	25.0%	12.5%		62.5%	12.5%	12.5%	12.5%
Dizzy Eyes Closed	37.5%	50.0%	12.5%		62.5%	12.5%	25.0%	
Vertigo	75.0%	25.0%			75.0%		25.0%	
Stomach Awareness	100.0%				75.0%	25.0%		
Burping	100.0%				100.0%			

Table 7. Glide vs Teleport Motion Sickness Results

Table 7 above shows the comparison between the reports of motion sickness across the teleport and “glide” navigation conditions. The colour indicates the level of severity while the percentage is out of the total number of participants. Blank cells indicate 0%. For example, 100% of participants reported no symptoms for “Stomach Awareness” for the teleport condition whereas 75% of respondents reported no symptoms in the “glide” condition with the remaining 25% of respondents reporting “Slight” symptoms.

Analysing the motion sickness responses across both conditions, it is clear to see that the “glide” condition resulted in more severe reports of motion sickness than the teleport condition. None of the symptoms were reported as "Severe" in the teleport condition while three (Headache, Eye Strain and Dizzy Eyes Open) in the "glide" condition were reported as "Severe" for 12.5% of respondents. The "glide" condition also had nine symptoms with "Moderate" reports of motion sickness whereas the teleport condition only had five symptoms with "Moderate" levels of motion sickness.

These results are consistent with the Sensory Conflict Theory because the condition where the participants could "see" themselves moving had a more severe effect on the participants than the condition where they could not see the movement. In other words, the condition that resulted in conflicting information coming from the vestibular and visual systems had a more adverse effect than the condition that did not have conflicting information. This indicates that it is the Sensory Conflict Theory that is the reason behind motion sickness occurring in the VR data visualisation.

In terms of how severe the effects were on all participants, while this is a relatively simple visualisation and for most participants the effects were at worst "Moderate", there is still a sample of the participants for whom motion sickness had a severe impact. This shows that simple VR data visualisations are enough to cause serious adverse effects in some participants and therefore it should be considered, and designed to be minimised, when creating VR data visualisations.

	Teleport First Group							
	Teleport Condition				Glide Condition			
	None	Slight	Moderate	Severe	None	Slight	Moderate	Severe
General Discomfort	50%	50%			50%	25%	25%	
Fatigue	75%	25%			50%	25%	25%	
Headache	75%		25%		75%			25%
Eye Strain	50%	25%	25%			75%		25%
DiffFocusing	25%	75%			25%	50%	25%	
Salivation	75%	25%			75%		25%	
Sweating	100%				75%	25%		
Nausea	100%				50%	50%		
Concentrating	75%	25%			75%	25%		
Sinus Pressure	75%	25%			75%		25%	
Blurred Vision	25%	50%	25%		25%	75%		
Dizzy Eyes Open	25%	50%	25%		50%	25%	25%	
Dizzy Eyes Closed	25%	50%	25%		50%		50%	
Vertigo	50%	50%			75%		25%	
Stomach Awareness	100%				75%	25%		
Burping	100%				100%			

Table 8. "Teleport First" Group Motion Sickness Results

	Glide First Group							
	Glide Condition				Teleport Condition			
	None	Slight	Moderate	Severe	None	Slight	Moderate	Severe
General Discomfort	25%	50%	25%		75%	25%		
Fatigue	50%	25%	25%		75%	25%		
Headache	50%	50%			100%			
Eye Strain	50%	50%			75%	25%		
DiffFocusing	25%	50%			100%			
Salivation	100%				100%			
Sweating	100%				75%	25%		
Nausea	50%	50%			75%	25%		
Concentrating	50%		25%		50%	50%		
Sinus Pressure	75%		25%		75%	25%		
Blurred Vision	50%	50%			75%	25%		
Dizzy Eyes Open	75%			25%	100%			
Dizzy Eyes Closed	75%	25%			50%	50%		
Vertigo	75%		25%		100%			
Stomach Awareness	75%	25%			100%			
Burping	100%				100%			

Table 9. "Glide First" Group Motion Sickness Results

Analysing the groups the participants were put into, either the "Teleport First Group" or the "Glide First Group", showed an interesting result. It was clear that the order the navigation conditions are experienced in has an effect on how severe the reports of motion sickness were for that condition. The most sickness-inducing condition of the two, the "glide" condition, has a more severe effect when it is experienced after the teleport condition than when it is experienced first. However, it is not the case where the condition experienced first results in the most severe reports of sickness. This is shown when the "glide" condition is experienced last it still has more severe results than the teleport condition that preceded it.

This is an interesting result, as it relates to the Sensory Conflict Theory, because the "glide" condition is at its most severe after the teleport condition is experienced. The Sensory Conflict Theory is still accurate because the "glide" condition still has the most severe effects overall. However, a question arises as to why is it the case that the most severe condition, when it's experienced first, doesn't result in the most severe reports of motion sickness? This is not explained by the Sensory Conflict Theory. A potential reason behind this is that experiencing the least taxing condition first makes the most taxing condition even more severe because the user was expecting the lower levels of motion sickness they experienced previously. This would also explain why the teleport condition is less taxing when experienced after the "glide" condition. After experiencing the more severe condition, the user is expecting that higher level of sickness again. The participants didn’t report the most severe sickness levels for the first condition across both groups because they didn’t know what to expect before the experiment began.

Another question from the groupings is why motion sickness for the teleport condition is reported as severe? There is no conflicting information coming from the senses so therefore there should have been little to no reports of motion sickness across both groups. Instead of little to no motion sickness as might be expected, some participants reported “Moderate” motion sickness symptoms. It can be assumed that if the visualisation was more complicated, the reports of moderate motion sickness could become severe motion sickness.

4.6 Conclusions

The overall effects of the two conditions suggests that the likely explanation for motion sickness occurring in VR data visualisations is the Sensory Conflict Theory. This explanation is confirmed as the “glide” condition caused more feelings of motion sickness than the teleport condition. In addition to this confirmation there were other interesting results. For example, the order in which the conditions were experienced in had an effect on motion sickness and the teleport condition across the two groups had different levels of motion sickness reported. In the “Teleport First Group” there were reports of motion sickness that were higher than what was expected; the expected levels being little to no motion sickness. One possible explanation for this is that, due to the “glide” condition being more detrimental in terms of motion sickness in general across both groups, being exposed to this condition first made the teleport condition easier in comparison. Starting with the more taxing condition (glide) may have made the teleport condition feel even less taxing than when starting with the less taxing (teleport) condition.

In terms of designing VR data visualisations to minimize the effect of motion sickness, the previous chapter does not address motion sickness when looking at a design process for VR; it is clear now that it is an important issue to be considered. As the results suggest, if there are multiple navigation conditions being used for a VR data visualisation, being given the more taxing one first results in less severe reports of motion sickness. If, however, there is only one navigation condition, these results suggest the Sensory Conflict Theory explains motion sickness in VR data visualisations and therefore removing any possibility of sending conflicting sensory information to the user will minimize the effects of motion sickness.

A potential limitation of this research could be overcome if different data sets were used for the different conditions. In this research, the “glide” condition and the “teleport” condition both had the same dataset which meant that once the tasks had been carried out for the first condition, they were completed much faster in the second condition. There is value and merit, though, in ensuring that the tests were as similar as possible. Another option is to use the same dataset and conduct the experiment over the period of a week where there is a significant gap between the two conditions. This could also negate the possibility of participants still experiencing the effects of motion sickness from the first condition.

This research has added to existing theory on motion sickness by showing that the Sensory Conflict Theory is relevant to and can explain motion sickness in VR data visualisations. This is supported by the results of this experiment which show the “glide” condition causes more severe motion sickness for the participants than the teleport condition as predicted by Sensory Conflict Theory. This can be summed up with the statement that seeing the movement but not actually moving is worse than not seeing the movement. An unusual finding was that the order in which the navigation conditions occur has an impact on motion sickness. While the teleport condition is less likely to cause motion sickness, it can still result in “Moderate” levels of motion sickness being reported when it is the first condition experienced. However, when it is experienced after the “glide” condition, the reports are much less severe. This suggests that if a user is unfamiliar with the visualisation environment then this can negatively affect their experience, and developers of VR data visualisations need to be cognizant of this when designing these systems. If there are multiple navigation conditions, exposing the user to the more taxing condition first should result in less severe motion sickness while if there is only one navigation condition then avoiding sending conflicting sensory information to the user is vital.

5. Conclusion

This thesis contains the work I conducted over the last 12 months in the State Street Advanced Technology Centre in UCC while studying for a research masters in the area of financial technology. The focus of my research was to contribute to the existing research body of knowledge on the topic of Virtual Reality (VR). I specifically focused on the three areas of data literacy, the design process, and motion sickness, as they relate to VR. An initial investigation into the relationship between data literacy and VR led to the formulation of a new design process for the creation of immersive data visualisations and finally to an experiment conducted on the effects of motion sickness in immersive data visualisations. Future research possibilities and implications as well as limitations of the current research are discussed in more detail in this conclusion.

5.1 Introduction

Due to the opportunity I received from this masters', I now have a better appreciation, knowledge and understanding of VR and the various possibilities of its potential applications. While I improved my academic skills through this research masters, I also gained invaluable experience of collaborating with State Street and working on a new and novel visualisation product with them. From this collaboration I gained more experience of working as part of a team and working to a number of deadlines to create the desired end product.

This section will conclude and summarize the work presented in this thesis. First, the research questions will be addressed and it will be explained how they were answered and what was learned from them. After this, the contributions to theory will be outlined; it will be stated how the research from this thesis adds to the theory surrounding VR, data literacy, VR visualisation design processes, and motion sickness in VR visualisations. The contribution to practice is then explained and how the research aids VR designers and users. The limitations of the research will be detailed before finally the future directions of the thesis are proposed.

5.2 Revisiting the Research Questions

Revisiting the three main research questions outlined in the Introduction of the thesis provides a summary of the insights gained throughout the study and are listed again as follows:

1. How does VR benefit the concept of data literacy?
2. How can the process for designing data visualisations be improved upon for immersive visualisations?
3. How much of an effect does motion sickness have in VR data visualisations and what is the potential reason behind what causes it?

The first question was examined in Chapter 2. A literature review was conducted on the various definitions of data literacy so that a concept centric matrix could be created. These key concepts were then categorized into two groups, termed “functional” and “imaginative” concepts. The “imaginative” concepts were then used in a comparison between traditional 2D visualisations and VR visualisations. This comparison illustrated how VR provides benefits to data literacy that are unique and which can’t be obtained from traditional visualisations. These unique improvements were then explained in more detail.

The second research question was the focus of Chapter 3. It was discovered that using a more traditional design process when developing an immersive visualisation was not suitable. Using this as the basis for the research, a novel design process for the creation of immersive data visualisations was produced that would reduce any reliability on trial and error techniques as well as improving efficiency in the design process. Through the use of the Design Science Research methodology, this design process was tested and refined and was critical in the establishment of the prototype visualisation.

The third research question was the focus of the Chapter 4. Through the creation of two identical immersive data visualisations with two different navigation conditions, one “glide” and one teleport, an experiment was created to determine the levels of motion sickness experienced by the participants. It also investigated the potential reasons behind the cause of motion sickness. Motion sickness was found through the use of the Simulator Sickness Questionnaire which was given to the participants after each condition was experienced and the applicability of various potential theories was discussed.

5.3 Contributions to Theory

This thesis contributes to research in the area of VR through a few different lenses: a theoretical application to data literacy, the theoretical development of a novel design process, and through an explanation of motion sickness in VR data visualisations. Contributions to the definitions of both ‘data literacy’ as well as ‘immersive visualisations’ were made before exploring how both can be augmented through the use of VR and an innovative design process respectively. Conducting a literature review and creating concept centric matrices of the terms ‘data literacy’ and ‘immersive visualisation development’ resulted in a more comprehensive understanding of what is important to both of these terms and where the most value could be added to these topics. Finally, a contribution was made to the field of motion sickness, the various terms associated with it, and a proposal is made in relation to the reason for its occurrence in VR data visualisations.

5.4 Contributions to Practice

This thesis was conducted where a number of applications of VR were examined so that there would be practical as well as theoretical benefits resulting from the research. The first contribution to practice, through the development of an immersive design process, is a more streamlined process that can be implemented by future immersive visualisation developers. Unlike more traditional design processes, it is specific to immersive visualisations and is more tailored to their creation. The second contribution is through the examination of navigation conditions in immersive visualisations. Through an experiment, it was interpreted that, while the teleport condition is less motion sickness-inducing than the “glide” condition, it can still result in significant reports of motion sickness and therefore caution is advised if it is to be implemented. In terms of suggesting a reason why motion sickness occurs in VR data visualisations, these results suggest that the Sensory Conflict Theory is the most likely reason. However, the often-severe reports of motion sickness resulting from the teleport condition would suggest that more research into this topic is required. The practical contributions of this thesis will be in the development of future immersive visualisations. The findings from the thesis could help immersive visualisation designers make their design processes more efficient, help them to understand how to generate more meaningful information from their visualisations, and aid them in understanding why and how severely motion sickness could be affecting their users.

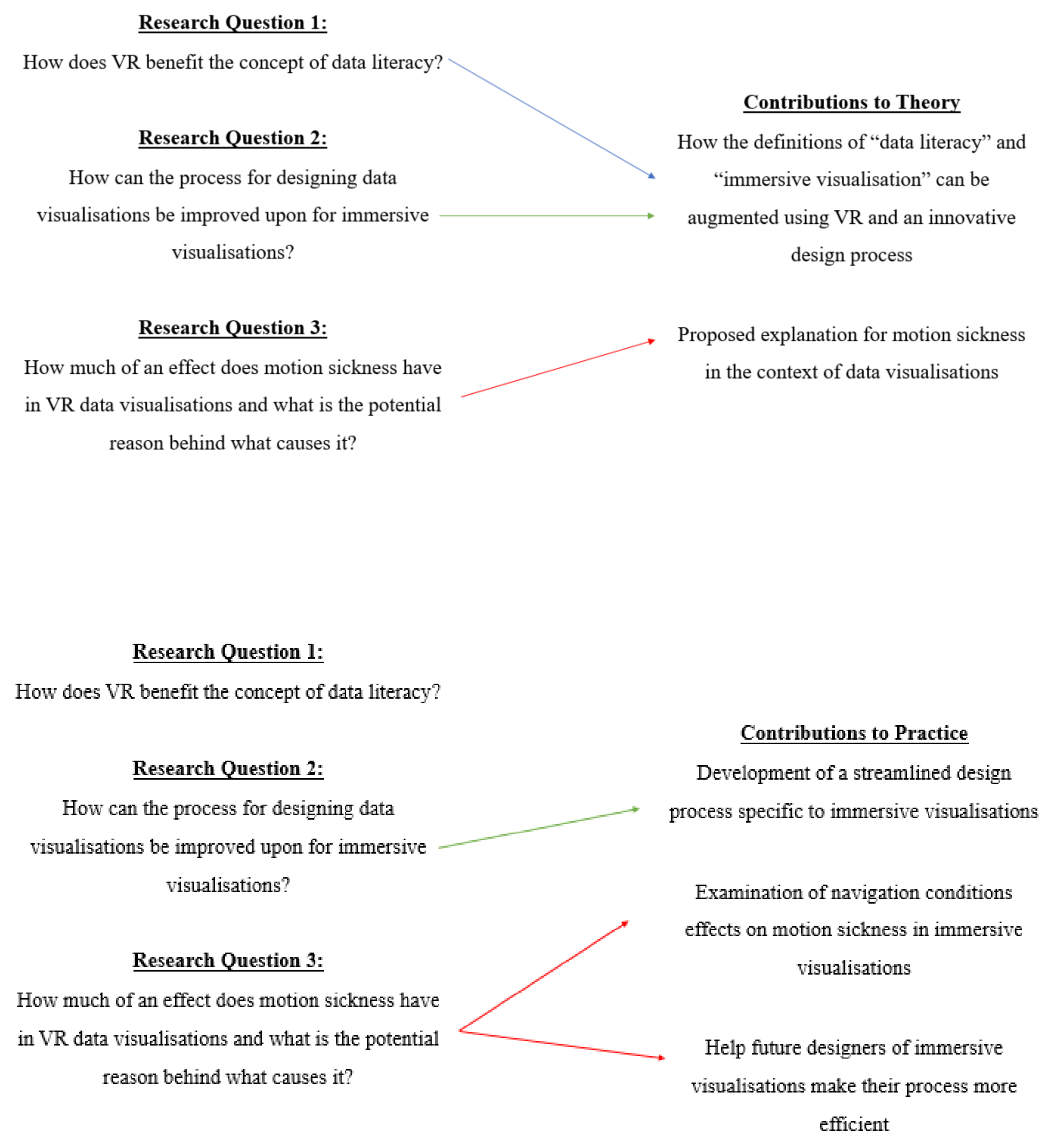


Figure 7. Relationship between Research Questions and Contributions to Theory and Practice

5.5 Limitations

As with any piece of research, there are limitations to this thesis that provide potential for future research.

In the creation of the new process for the design of VR data visualisations, only two iterations were possible. Given more time and more iterations, this could lead to an even more improved design process. Another limitation was that the process was only used on one prototype visualisation of financial products and services. Had the finalised iteration of the process been implemented for another prototype visualisation and/or a fully functioning visualisation to be used in industry, more insights could have been learned from these applications.

A limitation of the motion sickness study is the number of participants. While this study specifically focused on key informants, recreating the study with a greater number of participants could have resulted in more data being collected and a more diversified number of insights. A final limitation of this study is its focus on fully immersive, Virtual Reality (VR), visualisations. Had there been conditions in an Augmented Reality (AR) environment created in conjunction with the VR conditions, observations about the difference between the two technologies, and their levels of immersion, could have been deduced. While every effort was made to counteract these limitations, they do present opportunities for future research.

5.6 Future Research Directions

Future studies that could expand on the research would include applying the immersive design process to other visualisations in other industries. This would provide more concrete examples of the applicability of this process when used in varying contexts as well as determining if further improvements could be made. Another possible direction is to expand on the process as it is and to iterate on it further.

For the motion sickness study, further research could include increasing the number of participants with varying degrees of familiarity with 3D systems and computer usage. This would provide further insight into how severe the motion sickness is and if the experiences are felt differently by differing groups of people. Another potential research avenue is to apply the visualisation to Augmented Reality (AR) technologies in order to examine the difference between the two technologies for motion sickness.

Appendix 1

Studio In-Motion Questionnaire Page **1 of 4**

Simulator Sickness Questionnaire

Do you feel that you are in the same state good health as when you started the experiment? If you answered no please explain briefly in the space provided below: ☐ Yes ☐ No

For each of the following conditions, please circle how you are feeling right now, on the scale of *none* through *severe*.

1.	General discomfort	*none*	*slight*	*moderate*	*severe*
2.	Fatigue (weariness or exhaustion of the body)	*none*	*slight*	*moderate*	*severe*
3.	Headache	*none*	*slight*	*moderate*	*severe*
4.	Eye strain (weariness or soreness of the eyes)	*none*	*slight*	*moderate*	*severe*
5.	Difficulty focusing	*none*	*slight*	*moderate*	*severe*
6.	Increased salivation	*none*	*slight*	*moderate*	*severe*
7.	Sweating	*none*	*slight*	*moderate*	*severe*
8.	Nausea (stomach distress)	*none*	*slight*	*moderate*	*severe*
9.	Difficulty concentrating	*none*	*slight*	*moderate*	*severe*
10.	Fullness of head (sinus pressure)	*none*	*slight*	*moderate*	*severe*
11.	Blurred vision	*none*	*slight*	*moderate*	*severe*
12.	Dizzy (with eyes open)	*none*	*slight*	*moderate*	*severe*
13.	Dizzy (with eyes closed)	*none*	*slight*	*moderate*	*severe*
14.	Vertigo (surroundings seem to swirl)	*none*	*slight*	*moderate*	*severe*
15.	Stomach awareness (just a short feeling of nausea)	*none*	*slight*	*moderate*	*severe*
16.	Burping	*none*	*slight*	*moderate*	*severe*

If you expressed slight, moderate, or severe on any of the questions above, please state if you felt that way before using the system and if so, explain how you felt worse after using the system.

You should not drive an automobile for at least one half-hour after the end of the experiment.

Likert Scale

Mark a single box (*strongly disagree, disagree, undecided, agree,* or *strongly agree*) for each of questions below.

	strongly disagree	*disagree*	*undecided*	*agree*	*strongly agree*
I found the interface easy to learn.	☐	☐	☐	☐	☐
Once I learned the interface, I found the navigation to be easy and intuitive to use.	☐	☐	☐	☐	☐
Once I learned the interface, I found object manipulation easy and intuitive to use.	☐	☐	☐	☐	☐
Once I learned the interface, I found that I could focus on being creative instead of on the technicalities of the interface.	☐	☐	☐	☐	☐
I prefer the new interface to a mouse and keyboard interface.	☐	☐	☐	☐	☐
I was able to create the objects/scenes that I wanted.	☐	☐	☐	☐	☐
I would use the system myself in my home.	☐	☐	☐	☐	☐
I would recommend the system to friends.	☐	☐	☐	☐	☐
Overall, I enjoyed the experience.	☐	☐	☐	☐	☐

Demographic Information

1. Age and gender

   Age ______

   Gender ______

Background/Experience

For each question, please put a check next to your answer.

1. How often do you use a computer in your average week?

   I use computers less than . . .

   ☐ 1. 1 hour
   ☐ 2. 2 hours
   ☐ 3. 5 hours
   ☐ 4. 10 hours
   ☐ 5. 20 hours
   ☐ 6. 40 hours
   ☐ 7. more than 40 hours

2. Over the past two years, what is the most you have played video games in a single week? Select one.

   I played less than . . .

   ☐ 1. 1 hour
   ☐ 2. 2 hours
   ☐ 3. 5 hours
   ☐ 4. 10 hours
   ☐ 5. 20 hours
   ☐ 6. 40 hours
   ☐ 7. more than 40 hours

3. How many times have you used systems where yon did not use your hands in free 3D space to control the computer application (e.g., not using a keyboard, mouse, or touchscreen).

   Before today I used free 3D space interfaces . . .

   ☐ 1. Never
   ☐ 2. 1 time
   ☐ 3. 2 times
   ☐ 4. 5–10 times
   ☐ 5. 11–20 times
   ☐ 6. 20–100 times
   ☐ 7. nearly every day at school, at work, or for entertainment

4. How much experience do you have with CAD (Computer Aided Design) software (e.g., Maya, 3D Studio, Sketchup)

   Before today I used CAD . . .

   ☐ 1. Never
   ☐ 2. 1 time
   ☐ 3. 2 times
   ☐ 4. 5–10 times
   ☐ 5. 11–20 times
   ☐ 6. 20–100 times
   ☐ 7. nearly every day at school, at work, or for entertainment

Open-Ended Questions

1. What did you most like about the system?

2. How long did it take you to get good at using the system?

3. Were you able to create what you wanted to create?

4. Could you have created a more interesting scene given more time?

5. What did you dislike about the system?

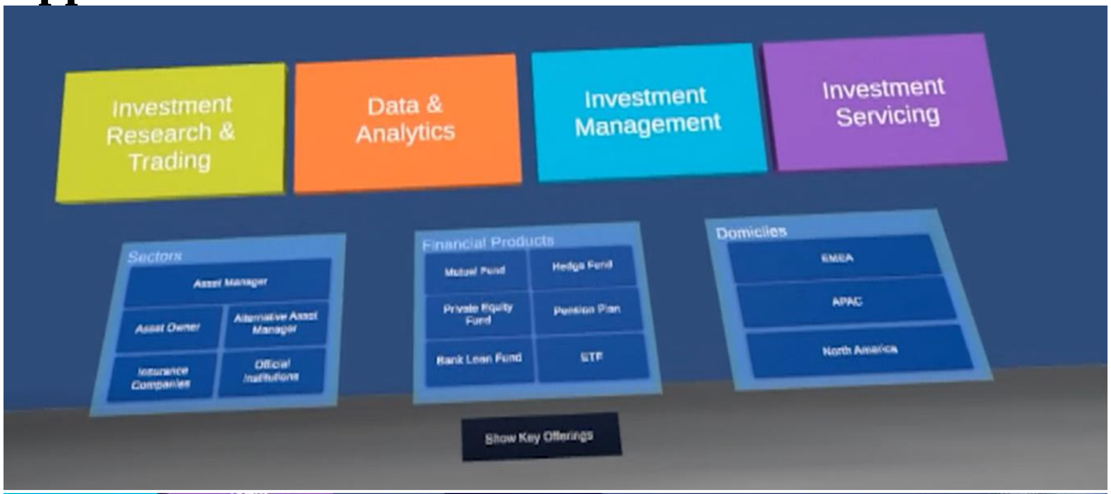
6. What suggestions or ideas do you have for improving the system?

7. Did you feel tired from using the systems? If so, in what areas of your body did you feel fatigue?

8. What do do you think consumers would pay for this system?

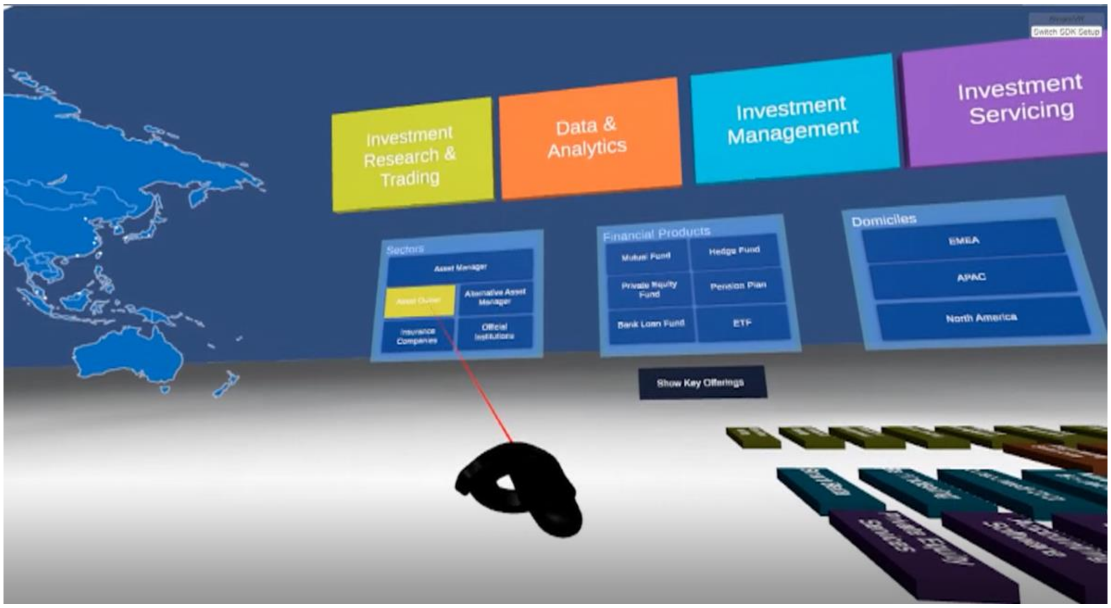
9. Any other comments?

Appendix 2



Investment Research & Trading
Data & Analytics
Investment Management
Investment Servicing
Sectors
Asset Manager
Asset Owner
Alternative Asset Manager
Insurance Companies
Official Institutions
Financial Products
Mutual Fund
Hedge Fund
Private Equity Fund
Pension Plan
Bank Loan Fund
ETF
Domiciles
EMEA
APAC
North America
Show Key Offerings

Servicing
Domiciles
APAC
North America
Global Trading
Foreign Exchange
Portfolio And Risk Analytics
Fund Administration
Multi Asset Solutions
Outsourced CIO
Local Government Pension Schemes
Market Entry Solutions
Accounting Software
Private Equity Services


Investment Research & Trading
Data & Analytics
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Insurance Companies
Official Institutions
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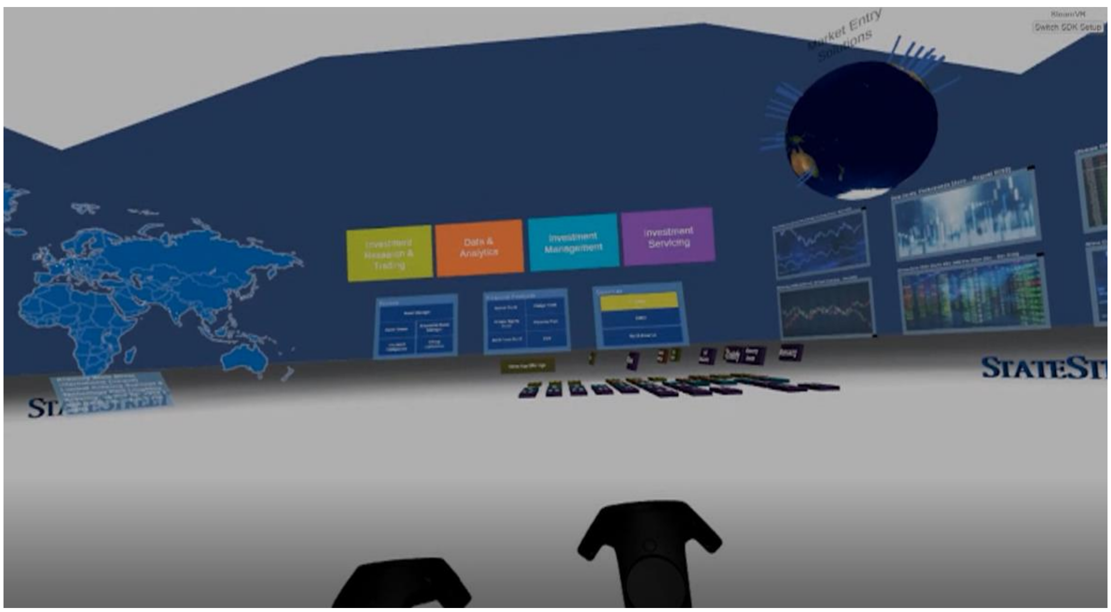
Mutual Fund
Hedge Fund
Private Equity Fund
Pension Plan
Bank Loan Fund
ETF
Domiciles
EMEA
APAC
North America
Show Key Offerings


Massachusetts State Street Corporation 100 Summer Street Boston, Massachusetts 02110 Tel: 617-786-3000 Mailing Address: Box 5501 Boston, Massachusetts 02206


Switch SDK Setup
iShares DAX DE ETF: Price movement (Jan – Dec 2018)
iShare Core FTSE UCITS ETF : Top 5 investor Domiciles (as at Dec
iShare Core FTSE UCITS ETF: NAV Per Share (Jan – Dec 2018)


Switch SDK Setup
Market Entry Solutions
Investment Research & Trading
Data & Analytics
Investment Management
Investment Servicing

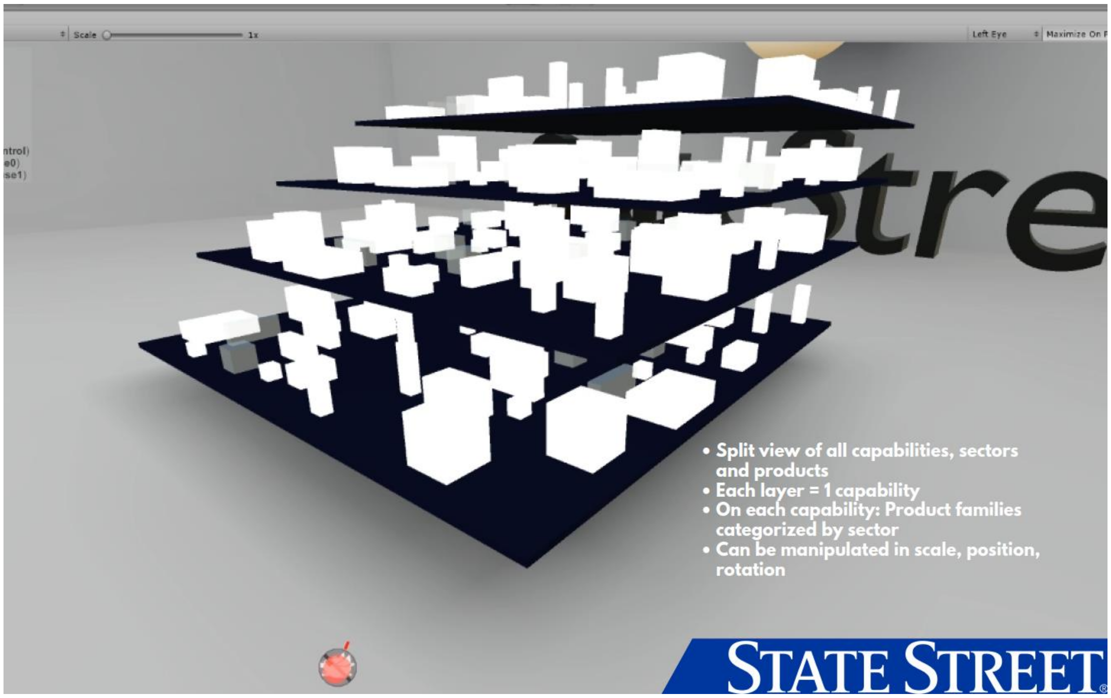
Appendix 3

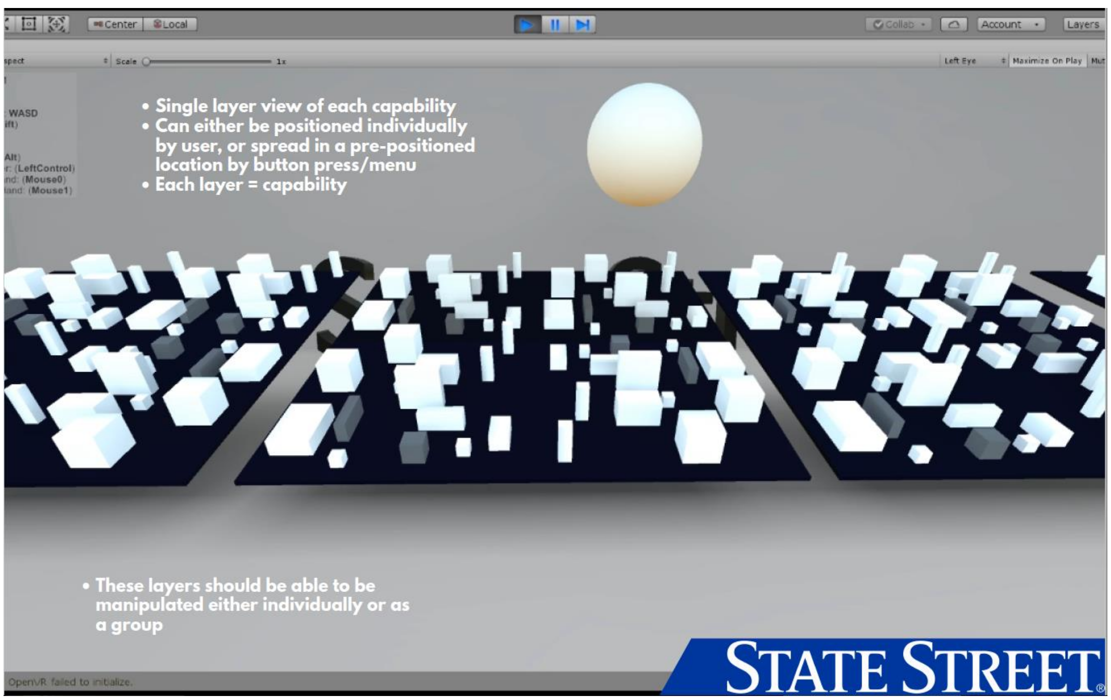
StateStreet Immersive Experience Storyboard
Alpha 0.1

J. Power, B. Scriven, U. Hill
2019

• Initial view after loading
• Globe showing StateStreet worldwide locations
• Compacted view of all capabilities/ sectors/products
• StateStreet Branding
StateStreet
• Users can use their real-world space or controller-controlled teleportation to move around the virtual space
STATE STREET

• Close view of compacted information
• Grid format: Capabilities on the X-axis; Sectors on the Y-axis
• Product-selection wheel either as floating menu or attached to user controller
STATE STREET


• Split view of all capabilities, sectors and products
• Each layer = 1 capability
• On each capability: Product families categorized by sector
• Can be manipulated in scale, position, rotation
STATE STREET


• Single layer view of each capability
• Can either be positioned individually by user, or spread in a pre-positioned location by button press/menu
• Each layer = capability
• These layers should be able to be manipulated either individually or as a group
STATE STREET


STATE STREET
VERUS
tateStr
• Single capability view
• Product families and sectors clear on single
• More granular view of product viewable when selected
• Audio & visual information presented on floating or popup screen when product selected
STATE STREET

Appendix 4


UCC
IMMERSIVE TECHNOLOGY
Researchers: J. Power, B. Scriven, U. Hill
THE STATE STREET IMMERSIVE EXPERIENCE
Built from the ground up, the State Street Immersive Experience was developed over the past 12 months at the State Street Advanced Technology Centre. Using the latest in virtual reality hardware and cutting edge software such as Unity, Steam VR and VRTK, the Immersive Experience was designed to showcase the potential of Immersive Technology to visualise the entire State Street catalogue of products and services in a single, consolidated location while also utilizing visualisation techniques previously never seen before.
VIRTUAL REALITY
In recent years, virtual reality technology has made quite a resurgence in popularity, mainly due to the exciting developments by companies such as HTC, Oculus and Valve. With advancements being made in VR hardware, these virtual technologies have started to become more accessible to not only the consumer, but also to businesses and organizations.
As such, more and more research is being performed in the area of virtual reality and companies like State Street are leading the way with industry usage of VR for a variety of new and exciting contexts. As more applicativons of VR in industry are investigated, we expect to see higher adoption of VR for real-world applications in previously unseen ways.
VIRTUALITY CONTINUUM
Mixed Reality (MR)
Real Environment
Augmented Reality (AR)
Augmented Virtuality (AV)
Virtual Environment
The Virtuality Continuum, coined by Paul Milgram, encapsulates all the potential environments we can experience on a spectrum. This ranges from entirely real environments, to completely virtual environments and everything in between. Our initial research lead us to grounding our analysis of immersive environments via the Virtuality Continuum, which allowed us to analyze various immersive environments and fit them along the virtuality continuum. This was paramount for consistent analysis and comparison between various immersive environments, technologies and methodologies.
While most commonly spoken about in terms of virtual and augmented reality, our research lead us to see many theoretical applications of augmented virtuality and mixed reality environments.
AUGMENTED REALITY
When most people think of immersive technology, their initial thought goes to that of virtual reality. However, augmented reality plays just as much of an important role in immersive technologies and currently has shown more potential for real-world applications than virtual reality.
Key players paving the way for augmented reality include companies like Microsoft and a plethora of mobile development as the improvements in smartphone hardware have enabled augmented reality apps for many different uses being developed over the last few years. From our research, augmented reality has shown huge potential in terms of augmented unlimited workspaces, collaboration and interactive manipulation of complex financial data.
DATA LITERACY
Data literacy is the concept of deriving meaningful, valuable information from a dataset. In modern day, we exist in a world where datasets grow exponentially year on year and as a result decision maker's level of data literacy have been stagnating or on the decline.
"Business decision maker's level of data literacy is insufficient in general"
(Economist Intelligence Unit survey, 2018)
Throughout our research, data literacy was a key concept as a measurement to improve efficiency in our visualisation methods. Developing a virtual environment to visualise complex State Street information and relationships was based around the goal of improving data literacy and providing an experience to showcase State Street information in a way that is not possible or highly inefficient with traditional visualisation methods.
POWERED BY
VRTK
STEAM VR
unity
Microsoft
htc
CU
BS
STATE STREET

Our Initial Research Goal

- Assess the current state of Immersive Technology, Data Visualization and Data Literacy Research
- Identify key areas of research for investigation
- Contribute to the existing body of Immersive Technology Research
- Develop a Proof of Concept Immersive Visualisation

The Papers

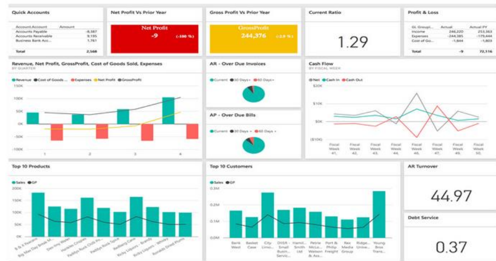
- "Improving Data Literacy Through the Use of Virtual Reality"
  - *Establishing the concept of data literacy, it's value and how it can be improved through the use of virtual reality*
- "Process for the Design of Immersive Data Visualizations"
  - *Creating a prescriptive process for designing visualizations specifically for immersive environments*

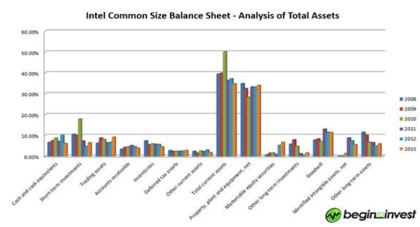
The Data Literacy Issue

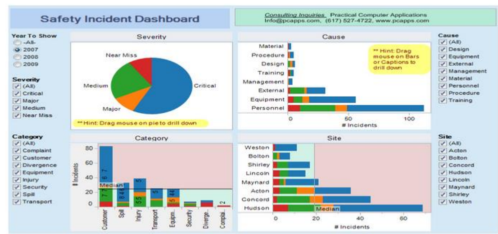
- Understanding, analyzing and deriving meaning
- Using this information to make better and more informed decisions
- Business decision maker's level of data literacy is insufficient in general
  (Economist Intelligence Unit survey, 2018)

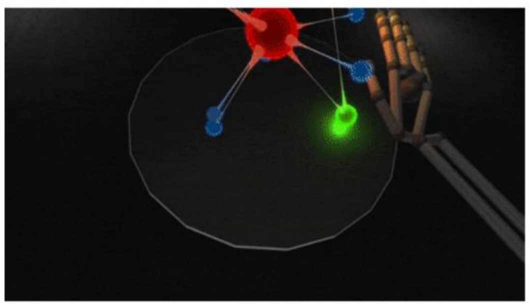
How does this relate to Data Visualization?

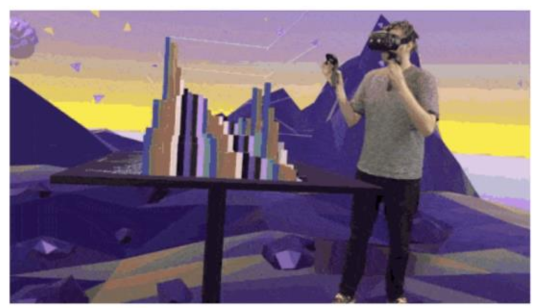
Traditional 2D Data Visualization





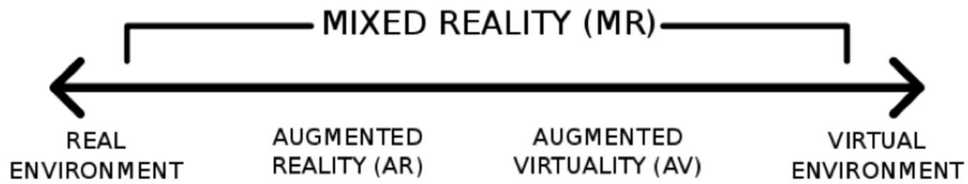






What is Immersive Technology?

What is Immersive Technology?



State of the Art

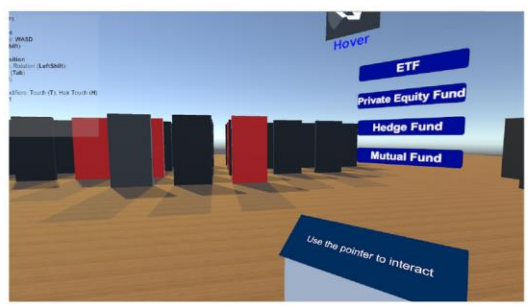
- Microsoft HoloLens 2
- Oculus Go - Wireless VR Headset
- Current Use Cases in Industry

Advantages

- Context
- Scale
- Dimensions
- Interactivity

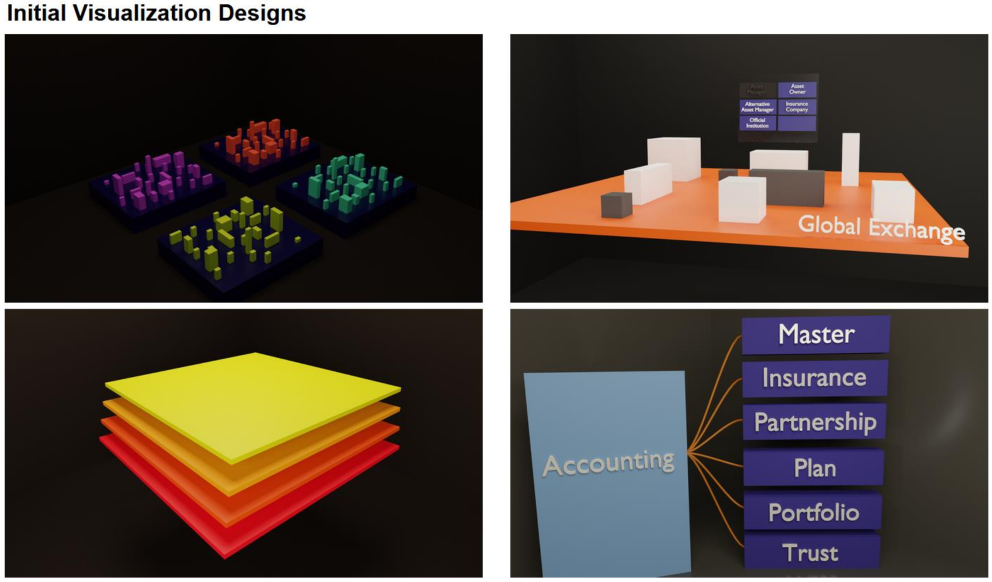
Disadvantages

- Motion Sickness
- Cost
- Bias

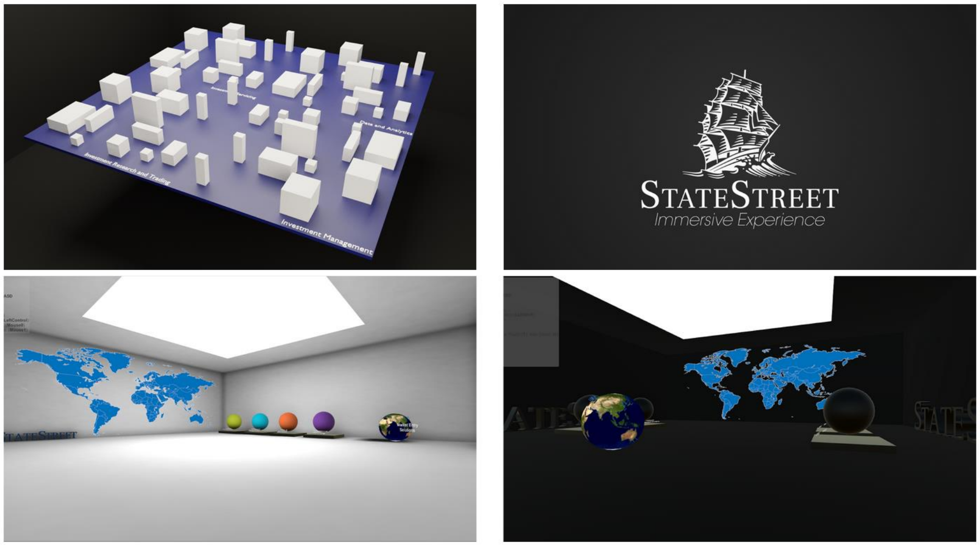


Creating Immersive Visualizations

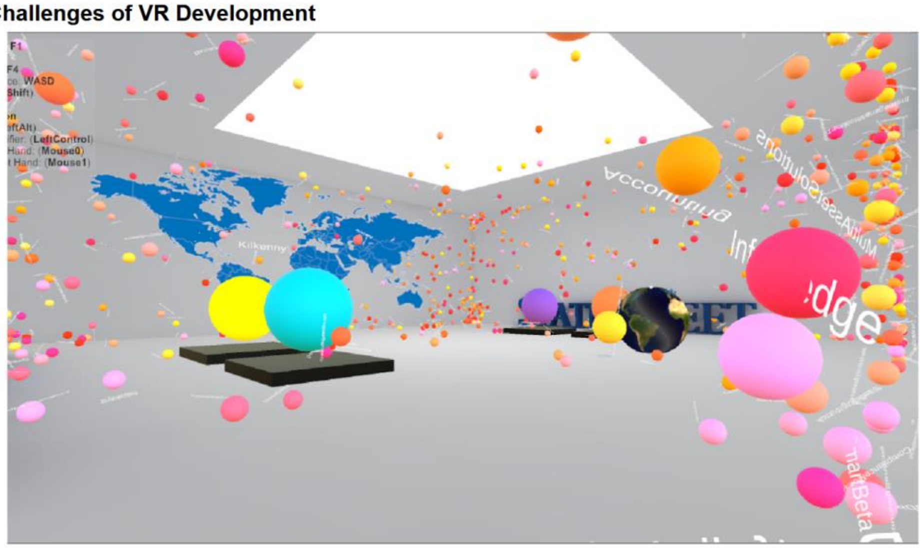
Initial Visualization Designs



Later Iterations



The Challenges of VR Development



Personal Findings

- Immersive Visualisation Design Process
- Difficulties encountered
- Solutions
- Benefits

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